AN EXPLORATION OF THE EFFECTS OF MAINTENANCE MANNING ON COMBAT MISSION READINESS (CMR) UTILIZING AGENT BASED MODELING

THESIS

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Captain, USAF

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Abstract

Agent based models have been shown to be powerful tools in describing processes and systems centered on individual behaviors and local interactions (i.e. “bottom-up”) between specific entities. Current application areas tend to be focused within the business and social science arenas, although their usefulness has been demonstrated in the modeling of various chemistry and physics-based systems.

Conversely, many highly process-oriented systems, such as manufacturing environments, tend to be modeled via “top-down” methods, including discrete or continuous event simulations among others. As a result, potentially critical attributes of the entities or resources modeled with these methods (spatial properties, “learning curve” or adaptability) may not be adequately captured or developed. This research develops an agent based model for application to a problem heretofore addressed solely via discrete event simulation or stochastic mathematical models. Specifically, a model is constructed to investigate the effects of differing levels of maintenance manning on sortie production capability, with an examination of those effects on the resulting Combat Mission Readiness (CMR) of a typical F-16 squadron.

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For my wife, without whose support this would never have been finished

Acknowledgments

I am sincerely grateful for the support and guidance I received from my faculty advisor, Dr. J.O. Miller. His loose hold on the reins allowed me to range far afield but ensured his insight and influence were always available. It has made the thesis experience extremely rewarding and memorable. I am also thankful to the rest of my thesis committee, Dr. Raymond Hill and Lt Col Stephen Chambal, both of whom provided valuable feedback and suggestions for improvement.

I am also indebted to the many maintenance professionals who provided their time and expertise, enabling me to accurately capture the critical processes necessary for my model. Special thanks goes to Capt Scott Hall and the men and women of the 20th AMXS, Shaw AFB, SC.

Adam S. MacKenzie

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AN EXPLORATION OF THE EFFECTS OF MAINTENANCE MANNING ON COMBAT MISSION READINESS (CMR) UTILIZING AGENT BASED MODELING

1. Introduction

1.1 Background

The Air Force possesses the singular ability to "project national influence anywhere in the world" on very short notice (AFDD-1, 2003). This is accomplished via the application of a broad spectrum of capabilities, with the end goal to be ever-ready to meet the needs both of our National leaders as well as the combatant commanders (Air Force Posture Statement, 2009). The Air Force's primary force application tool is the aircraft or spacecraft, which are operated and supported by a host of personnel across a variety of organizations.

Substantial time expenditures in both training and maintenance activities are required to ensure the constant readiness of both the operators and support personnel to support mission taskings. As with any complex organization, metrics have been established for leaders to gauge progression and measure status of processes and systems critical to mission accomplishment. A key metric used by leadership to gauge the service's instantaneous level of readiness to apply airpower is Combat Mission Readiness (CMR). Specifically, CMR is defined as "the minimum training required for pilots to be qualified and proficient in all of the primary missions tasked to their assigned unit and weapons system" (AFI 11-2F-16V1, 2007).

An analysis was performed on CMR in response to a tasking by the commander of United States Air Forces in Europe (USAFE) (Lipina, 2009). While not an exact measure of specific ability levels, the CMR metric provides leadership a top-level view of a unit's overall readiness to execute their assigned mission at any given time. Lipina's research developed a regression model to determine the major factors driving CMR. His results showed that CMR depended in large part on availability of qualified aircraft maintenance manpower.

Currently, the active duty enlisted aircraft maintenance workforce makes up a little over 27% of the Air Force's total active enlisted end-strength (AF Personnel Center, 2009). This figure encompasses Airmen at all skill levels and with Air Force Specialty Codes (AFSCs) beginning with:

- 2A – Manned Aerospace Maintenance
- 2P – Precision Measurement Equipment Laboratory
- 2R – Maintenance Management
- 2W – Munitions and Weapons (Air Force Enlisted Classification Directory, 2009)

This 27% figure can easily be inflated when one considers the airmen involved in delivery of fuel, mission planning or supply chain management/parts delivery; the above grouping of AFSCs is representative of what would be contained in a typical Maintenance Group.

Directly related to finding CMR's dependence on skilled maintenance technician availability was Lipina's discovery of annual flying hour program requests from a variety of bases. Specifically, in fiscal 2009, fighter wings across USAFE requested less flying hours than were actually required to maintain the minimum proficiency levels required for each unit to ensure each of their pilots remained CMR. In fact, each unit requested only the number of sorties/hours that their respective Maintenance Groups stated they could produce. This fact supports Lipina's regression study results; a unit's ability to maintain their CMR rates is directly tied to maintenance's ability to provide sufficient mission-ready aircraft. This thesis explores this specific relationship by modeling the effects of varied levels of manning on a maintenance unit's sortie generation capabilities.

1.2 Problem Statement

There are currently no models of the sortie generation process that account for the adaptive nature of the extremely complex maintenance process. Specifically, no models consider the effects of various skill levels on unit productivity. This research examines the potential application of agent-based modeling (ABM) techniques to explore the impacts and contributions of maintenance manpower to sortie production and, ultimately, combat mission readiness.

1.3 Scope

The sortie generation process at a unit level is a complex set of processes with a variety of stochastic elements and influences from multiple sources. Each of the impactors and influences in the overall process can be considered a self-contained "unit".

Whether one contemplates the individual electrician or crew chief on the flight line, the supply troop in the Logistics Readiness Squadron, or even the aircraft being worked or the parts being moved up and down the supply chain, each individual plays a fundamental role in the overall process. Additionally, while the behaviors and motivations of each of these constituent units is relatively well understood, the resulting behavior of the system as a whole is more complex than any explanation any individual component could provide. This is a hallmark of a complex system (Flake, 2002), an environment well suited to an ABM's ability to reveal "properties of systems that are not properties of the agents themselves" (Jones, 2007).

1.4 Background on ABM

ABM is a relatively new approach to the simulation of complex systems. Instances such as Conway's 1970 "Game of Life" notwithstanding, the use of agent based modeling techniques really began to gain prominence in the mid 1980's, as computational power became more and more available. Typically, these methods have been applied to the social and physical sciences, encompassing everything from basic social interactions to epidemiological studies to detailed physics-based models of gas particle diffusion. More recently, ABM modeling techniques are being applied to problems such as power distribution networks and economic markets that have historically been modeled utilizing other more aggregate methods (Macal & North, 2005). Within the Department of Defense (DoD), ABMs have become widely used for combat simulations, but in general, application to the logistics domain, and specifically military logistics, is still a fairly new concept (Tripp et al, 2006). Work in the past decade has applied ABMs to supply chain management (Krishnamurthy et al, 2008), and Tripp notes that these and similar research efforts are critical in advancing the DoD's capability to implement advanced combat support processes. The Marine Corps Warfighting Laboratory's Project Albert is another significant effort within the DoD that made use of agent based models. While much of the research was geared toward in-depth explorations of combat operations and situations (Project Albert, 2010), research was performed on the effect of troop quality on combat effectiveness (Engleback et al, 2003). This is directly translatable to the research and methodology described in this thesis.

The sortie generation problem is not new. There has been a host of research performed on the issue with objectives spanning everything from general system observation and characterization to attempts to optimize one or more constituent sub-processes within the overall sortie generation process. These research efforts have employed many methods, including discrete event simulation (Faas, 2003; Iakovidis, 2005), Markov decision analysis (Dietz, 1991) and neural networks (Dagg, 1991). Some of these have even addressed the specific issue of maintenance manning and its potential effects on sortie production and overall readiness (Gotz and Stanton, 1986). However, only a single paper was located that dealt specifically with the dynamics of the system as influenced by maintenance skill levels (Garcia and Racher, 1981). Regardless, the methodologies utilized to date follow a more traditional approach of decomposing the system under investigation and attempting to describe its behavior as the "sum of its parts", which has been shown to be "inadequate to model and analyze" some large and complex systems (Kaegi et al, 2009). In fact, research performed across multiple disciplines has shown that these traditional methods of system decomposition and subsequent reconstitution can prove not only inadequate but also potentially produce misleading results (Bobashev et al, 2007). Kaegi et al (2009) further argue that in these situations, ABM has a “high potential to help realistically model large and complex systems”.

1.4.1 What is an Agent?

All of the literature reviewed agrees on one thing; there is no agreed-upon definition of what constitutes an agent. Franklin and Graesser (1997) provide an excellent overview of a variety of definitions of what constitutes an agent, and their “Maes Agent” is definitely germane to this specific problem:

> Autonomous agents are computational systems that inhabit some complex dynamic environment, sense and act autonomously in this environment, and by doing so realize a set of goals or tasks for which they are designed. (Franklin and Graesser, 1997)

Another description labels agents as “autonomous decision-making entities”, each of which “individually assesses its situation and makes decisions based on a set of rules” (Bonabeau, 2002). The common thread throughout the majority of definitions of agents is the idea of autonomy, namely that each of these entities is not a passive observer or passive follower of directions, but rather an active unit executing its own set of behaviors.

An additional critical property of agents is their collective ability to exhibit complex patterns of behavior that might not have been readily evident when contemplating the properties of the individual agents themselves. These so-called "emergent behaviors" (Gilbert and Terna, 1999) are a product not only of the behaviors of each of the individual agents, but also of the means by which the agents interact and the level of interaction stemming from their individual behaviors.

All models are an abstraction of a system utilizing some means of aggregation to describe system behaviors. ABM's focus on the behaviors of individual entities, or "agents", allow it to capture interactions between distinct individuals or groups. In the context of the sortie generation process, this includes, among other things, the skill levels and related efficiency of individual maintainers and the change in system response as each individual "learns" how to better execute their job. While this may be a relatively simplistic example, the more traditional modeling techniques utilized in the past fail to capture this level of system detail, instead relying on either static values or "one-size-fits-all"-fitted theoretical distributions aimed at providing the aggregated swath of "most likely" values.

Exploring the sortie generation and maintenance manning problems with ABM techniques provides a theoretical counterpoint to the previous body of work. In applying these new techniques, new insight can be gained into both the internal system behaviors and resulting system responses. Additionally, a successful modeling effort will indicate that these techniques are not only applicable to this body of problems, but might also be preferable, both due to its ability to capture emergent phenomena and its touted flexibility as a modeling domain (Bonabeau, 2002).

1.5 Why Sortie Generation?

Despite a multitude of mission areas covering a broad spectrum of domains, the Air Force remains a predominantly aerospace-focused service. Specific to this research, an individual unit's CMR rates are direct results of the number of Ready Aircrew Program (RAP)-coded sorties successfully completed by aircrews each month (AFI11-2F-16 V1, 2007). A unit's ability to successfully generate sorties holds a prominent position among the key factors affecting RAP completion and, subsequently, CMR.

Figure 1 provides a top-level view of the sortie generation flow. The process is typically considered to start with the recovery of an aircraft from a previous mission (AFI21-101, 2006). After completion of recovery actions and placing the aircraft on a parking spot, the aircraft is serviced and the aircrew provides details of any issues encountered during flight. Depending on the severity, or if items are discovered during servicing operations, unscheduled maintenance actions are initiated. Depending on necessity and resource availability (time, parts, technicians, etc.) preventative maintenance measures may also be started at this point. While schedules are typically set at least a week ahead of time, some online changes may need to be made at this point due to aircraft status changes. The aircraft is reconfigured for its next mission, receives a set of inspections, and is then launched on its next sortie.

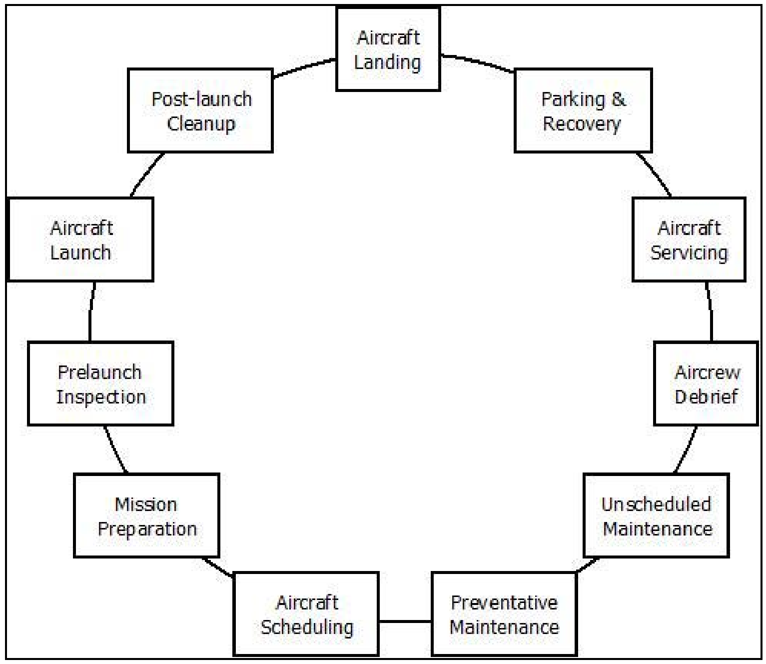

Figure 1 - Sortie Generation Process (Faas, 2003)

Each of the sub-process blocks in Figure 1 is a self-contained complex procedure and depends on a variety of internal (various flight-line maintenance specialties) and external (supply, fuel delivery, etc.) stakeholders. Not all of these sub-processes are explicitly modeled in this research.

1.6 Methodology

The current model was developed around the sortie generation process and centers on activities performed by a typical Aircraft Maintenance Squadron. This aligns with the research's primary focus on a unit's operational readiness as a function of maintenance manning levels. The focus is not on preventive or off-equipment maintenance tasks even though such efforts do support the overall goal of operational and combat readiness. However, with many of the measures centered around sortie production rates and the activities related to this production, it was natural to scope the research to a single area within a Maintenance Group. This scoping is not unusual (Lipina, 2009; Chimka and Nachtmann, 2007). This research also extends previous work in the same area (Lipina, 2009), which focused on a single unit. Due to Lipina's focus, and work with Spangdahlem AB, the same flying unit was selected, both to serve as a point of comparison, and since a multitude of data was readily available.

The body of previous work revealed very few analyses of the effects of maintenance technician expertise on sortie production. Chimka and Nachtman (2007) provide a regression study on which manning factors were used to forecast fleet health metrics. Garcia and Racher (1981) examined the influences of skill levels within a maintenance setting. Their work focused on a single set of Air Force Specialty Codes (AFSCs) and a methodology to modify the Logistics Composite Model (LCOM) to account for differences in skill sets. They concluded that the skill levels of maintainers significantly affected the productivity of a maintenance workcenter. This supports the hypothesis that an analysis of a maintenance workforce should include the effects due to skill level mix.

LCOM is a "statistical simulation model that the Air Force uses to estimate monthly man-hours and shift manning required to accomplish direct maintenance tasks" (Dahlman et al, 2002). Simply put, it is a non-agent-based simulation tool used by the Air Force to determine the appropriate manning for a maintenance unit, based on a detailed simulation of aircraft and supporting maintenance operations at the unit level.

While the capability exists to implement “work arounds” to model the effects of various skill levels on fix times, etc., this requires the user to modify the detailed task network definitions within LCOM. These modifications establish lower skill levels as allowable substitutions for tasks, and then apply task multipliers when those substitutions are made. Besides being cumbersome to employ, these approaches fail to effectively capture the resources being applied for on the job training (OJT) during task execution, and also fail to depict the ability for technicians to “learn” and improve in efficiency over time. The fact remains, LCOM “does not explicitly account for OJT or experience mix” (Dahlman et al, 2002), and the emergent behavior of the overall system as each maintainer improves in efficiency and productivity over time make this an excellent problem to be tackled with an ABM.

1.7 Model Construction

Law (2007) provides a framework for designing a simulation study; his method was used as a guide. Figure 2 details the study design flow.

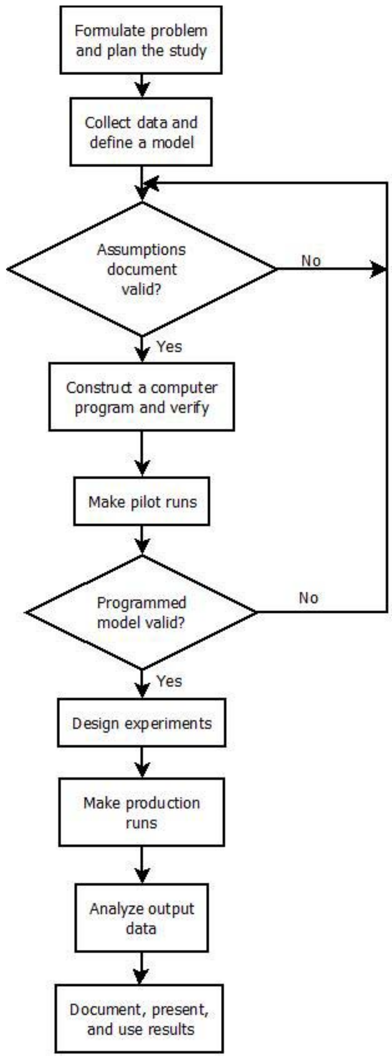

Figure 2 - Steps in a Simulation Study (Law, 2007)

The modeling process begins with a general layout of the logic and process flows involved. This macro-level flow is developed based on personal experience, with some details on idiosyncrasies of fighter aircraft maintenance procedures provided by interviews with AFIT graduate students with background in maintenance of fighter aircraft, and maintenance technicians in the field. The overall model flow is a sub-set of the top-level sortie generation process depicted in Figure 1, and is included in Figure 3.

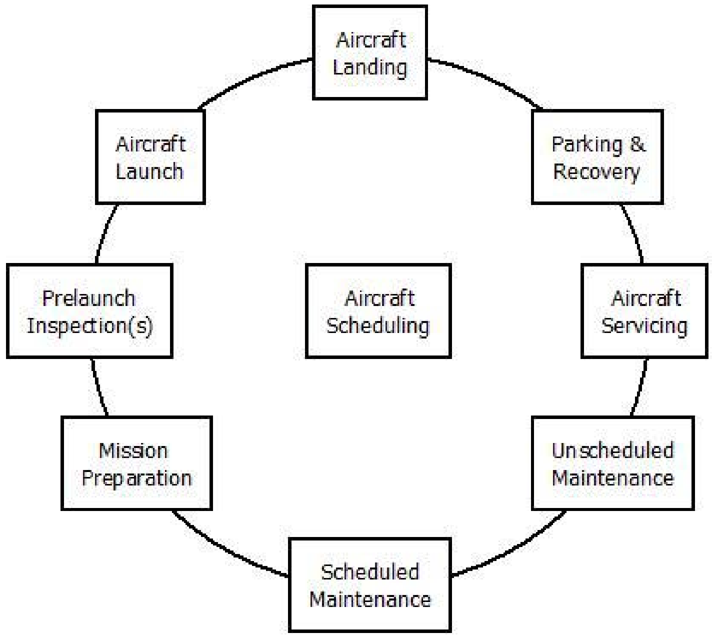

Figure 3 - Modeled Sortie Generation Flow

Figure 3 shows that the modeled sortie generation flow includes all but two of the top level flow process blocks as proposed by Faas (2003) (see Figure 1). Additionally, the "Aircraft Scheduling" block is moved to the center of the graph. This represents the scheduling of individual aircraft as a continuously executed task.

This model was developed on a "ground-up" framework, using an agent-based modeling environment called NetLogo, developed at Northwestern University (Wilensky, 1999). The development environment was selected based on ease of use and the system's operating characteristics (Railsback et al., 2006). One chief concern was the robustness of the random number generator, and the ability of the system to designate separate and distinct random number seeds to specific processes in order to implement common random numbers as a variance reduction technique during the analysis period. The

NetLogo system did not have the capability to track more than a single random number seed at a time. A JAVA-based extension was developed to add this capability (all source code and executables are available upon coordination with AFIT). The random number generator used in the NetLogo environment is the Mersenne twister, proposed by Matsumoto and Nishimura (1998). An in-depth statistical evaluation is performed in (L'Ecuyer, 2001) and the generator was found to perform as well as generators used in a variety of commercial simulation software packages.

To develop the model framework, the overarching process flows were abandoned in favor of "behavior" models for each of the identified agents. In this model, there were 4 identified Agent types. These were:

- **Maintainers –** Each maintainer was defined based on their AFSC, to include:
  - Crew Chief (CC),
  - Avionics,
  - Electro-Environmental (EE), and
  - Propulsion (Prop).

Each of these were then further classified by skill level (3-level Apprentices, 5-level Journeymen and 7-level Craftsmen). AFI 36-2101 (2009) provides key characteristics for each skill level:

- 3-level: "basic knowledge in their AFSC through completion of initial skills training",
- 5-level: "demonstrated skilled proficiency in their AFSC", and

- 7-level: “high degree of technical knowledge within their AFSC and…have acquired supervisory capability through training and experience”.

- **Production Superintendent (Pro Super) –** The pro super directs the unit’s overall maintenance effort.
- **Expediters –** Expediters work directly for the pro super and ensure maintenance is accomplished, managing their assigned pools of resources (personnel) to meet the pro super’s direction. The three sub-types are:
  - Crew Chief Expediter
  - Mechanical Expediter (EE, Prop, Hydro)
  - Avionics (Comm/Nav, GAC)
- **Aircraft –** Aircraft agents within the model are simple entities with no real behaviors of note. These entities serve to provide tangible targets for the maintenance agents, as well as holding a variety of variables that support the overall logic flow of the model.

Chapter 2 provides details on the development of the model and various analytical results. Chapter 3 presents an application of the model to a representative case study focused on a single “typical” aircraft maintenance unit, along with numerical results. Chapter 4 concludes the thesis, highlighting significant findings and identifying areas for future study. Note Chapters 2 and 3 are structured as standalone papers.

2. Application of Agent Based Modeling to the Sortie Generation Problem

2.1 Overview

Substantial time expenditures for both training and maintenance activities are required to ensure the constant readiness of operators and support personnel to support mission taskings within the United States Air Force. As with any complex organization, metrics have been established for leaders to gauge progression and measure status of processes and systems critical to mission accomplishment. A key metric used by leadership to gauge the service's instantaneous level of readiness to apply airpower is Combat Mission Readiness (CMR). Specifically, CMR is defined as "the minimum training required for pilots to be qualified and proficient in all of the primary missions tasked to their assigned unit and weapons system" (AFI 11-2F-16V1, 2007).

An analysis was performed on CMR in response to a tasking by the commander of United States Air Forces in Europe (USAFE) (Lipina, 2009). While not an exact measure of specific ability levels, the CMR metric provides leadership a top-level view of a unit's overall readiness to execute their assigned mission at any given time. Lipina's research developed a regression model to determine the major factors driving CMR. His results showed that CMR depended in large part on availability of qualified aircraft maintenance manpower.

This research develops an agent-based simulation model for application to the sortie generation process, focused on an individual unit. The simulation includes representations of each individual maintainer within the unit, along with supervisory agents that provide direction in the form of task prioritization and resource assignment. Using a high-fidelity depiction of each entity, an exploration of the effects of different mixes of skill levels and Air Force Specialty Codes (AFSCs) on sortie production is performed. The model development was executed in three distinct phases:

- Agent definition,
- Supporting data extraction and filtering, and
- Model coding and supporting logic development.

The sortie generation problem is not new. There has been a host of research performed on the issue with objectives spanning everything from general system observation and characterization to attempts to optimize one or more constituent sub-processes within the overall sortie generation process. These research efforts have employed many methods, including discrete event simulation (Faas, 2003; Iakovidis, 2005), Markov decision analysis (Dietz, 1991) and neural networks (Dagg, 1991). Some of these efforts have even addressed the specific issue of maintenance manning and its potential effects on sortie production and overall readiness (Gotz and Stanton, 1986). Regardless, the methodologies utilized follow a more traditional approach of decomposing the system under investigation and attempting to describe its behavior as the "sum of its parts", which has been shown to be "inadequate to model and analyze" some large and complex systems (Kaegi et al, 2009). In fact, research performed across multiple disciplines has shown that these traditional methods of system decomposition and subsequent reconstitution can prove not only inadequate but also can potentially produce misleading results (Bobashev et al, 2007). Kaegi et al (2009) further argue that in these situations, ABM has a “high potential to help realistically model large and complex systems”.

2.2 Agent Development

The power of the agent-based model environment lies in its ability to codify a specific agent’s decision-making processes into behaviors (often as simple rule-sets) and then observe the agents as they “autonomously” react and interact with other agents and their environment, potentially collectively producing “emergent behaviors” that might not otherwise have been either observed or predicted based on other methods of analysis (Bonabeau, 2002). In the case of the current model, specific logic flows were mapped for each agent type, similar to the process used when developing the general flow. Each flow was developed using the agent’s point of view and level of global “awareness”, which varied depending on the agent type. In the interest of standardization and readibility of the agent descriptions, details on each of the agent types are provided below in accordance with applicable sections of the *Overview, Design Concepts and Details* (ODD) protocol (Grimm et al. 2006).

2.2.1 Aircraft Agents

Each aircraft agent is a purely reactive entity. It contains attributes that track completion of preflights, sortie counts, and current status among other things, but does not employ any active decision-making functions. Based on data obtained from

Spangdahlem AB, 22 aircraft were incorporated into the model. Break, abort and other data measuring failures of the aircraft were gathered and utilized to construct empirical and/or theoretical distributions for use in describing the stochastic nature of the various failure mechanisms affecting each aircraft.

The aircraft agent has two system states: non mission capable (NMC) and mission capable (FMC). No partially mission capable (PMC) state is included (Ciarallo et al (2005) do model PMC states for mobility aircraft). This was done to simplify the overall state space of the model, and since the other logic mechanisms do not require the addition of a third state. Figure 4 provides the modeled flows for aircraft agents.

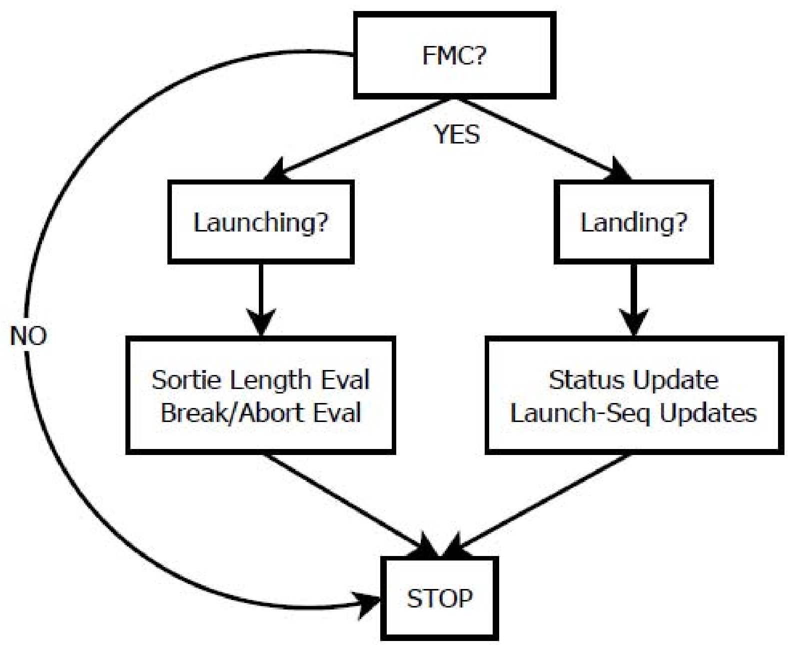

Figure 4 - Aircraft Agent Logic

2.2.2 Production Supervisor Agent

As defined in AFI 21-101 (2006), the production supervisor (Pro Super) is responsible for directing "the overall maintenance effort of their unit." As such, the Pro Super agent is the only one with true global awareness, and makes the majority of decisions within the simulation. These include:

- Job priorities as they arise,
- Which aircraft are to be put into the flying schedule,
- How many and which aircraft are to be generated as spares, and
- When to begin work on what aircraft.

The Pro Super has two states: available/planning and exceptional release (ER) signoff. In the former, he is performing each of the tasks outlined above every time step. For the latter, he is considered unavailable while signing the ER. As the individual with overall responsibility for maintenance execution, the Pro Supers' signing of the ER "serves as certification…that the [aircraft] is safe for flight" (TO 00-20-1, 2006) and is required prior to each sortie. Figure 5 depicts the Pro Super agent logic.

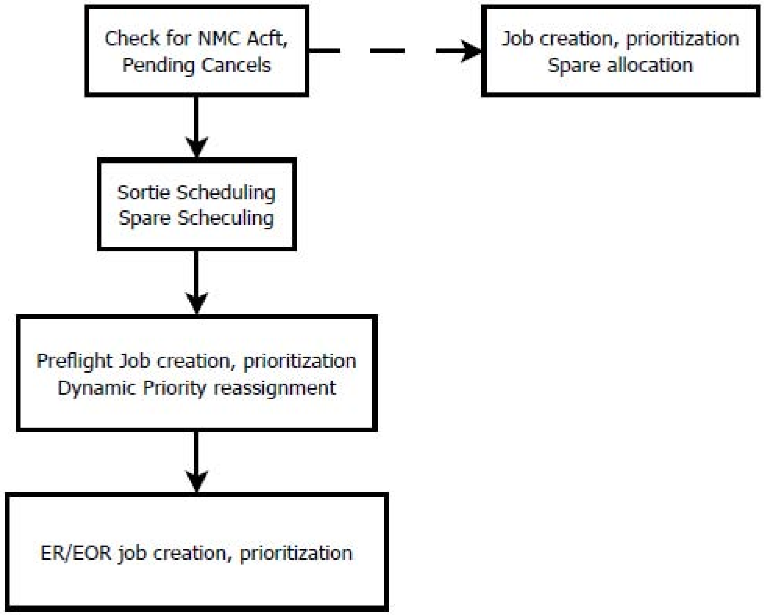

Figure 5 - Pro Super Agent Logic

2.2.3 Expediter Agents

Each of the three expediter agents have a reduced level of global awareness. The crew chief expediter is specifically aware of any impending aircraft landings, since aircraft tend to be recovered by crew chief personnel. Expediters also perform the allocation of maintenance technicians to tasks based on the task's priority as assigned by the production superintendent agent. By definition, expediters "work for the Pro Super and manage, control and direct resources" in order to "ensure maintenance is accomplished" (AFI 21-101, 2006). Within their execution time step, each of the expediters scan for jobs in the system (taskings from the production superintendent), and if any are found for the AFSCs they are responsible for (note above that each expediter is responsible for a specific subset of the overall mix of maintenance AFSCs) they proceed with their job assignment logic.

For expediters to assign a task to a group of maintainers, they must first determine if sufficient manpower is currently available. One key consideration is the number of maintainers required for each job. In many cases, specific tasks carry technical order requirements for minimum crew sizes. While the current model does not include sufficient detail to capture the actual task-level crew-size requirements, this influence is captured by treating crew size as a random variable and drawing from an empirical distribution based on two years worth of data from Spangdahlem AB. This determines crew size based on the work unit code (WUC) of the job and the AFSC assigned to work the job. Depending on the priority of the task and the availability of personnel working lower priority jobs, the expediter may:

- Pull personnel from lower priority jobs,
- Delay the job, or
- Work the job with the available (sub-optimal) manpower with a penalty on job time.

Additionally, when assigning a job, expediters must also determine when to allow training to occur, and whether or not training (when allowed) will occur. This is determined based on the priority of the job (priority one jobs do not allow for training) and the skill level of the initially assigned team. Once a fully qualified (5 and 7 levels) team has been selected by the expediter, a random draw is evaluated against the lowest efficiency value on the qualified team (see section below for efficiency value). If the random number is lower, then training is permitted to occur and up to two 3-levels are randomly selected to be trained. The Expediter agent logic is included below in Figure 6.

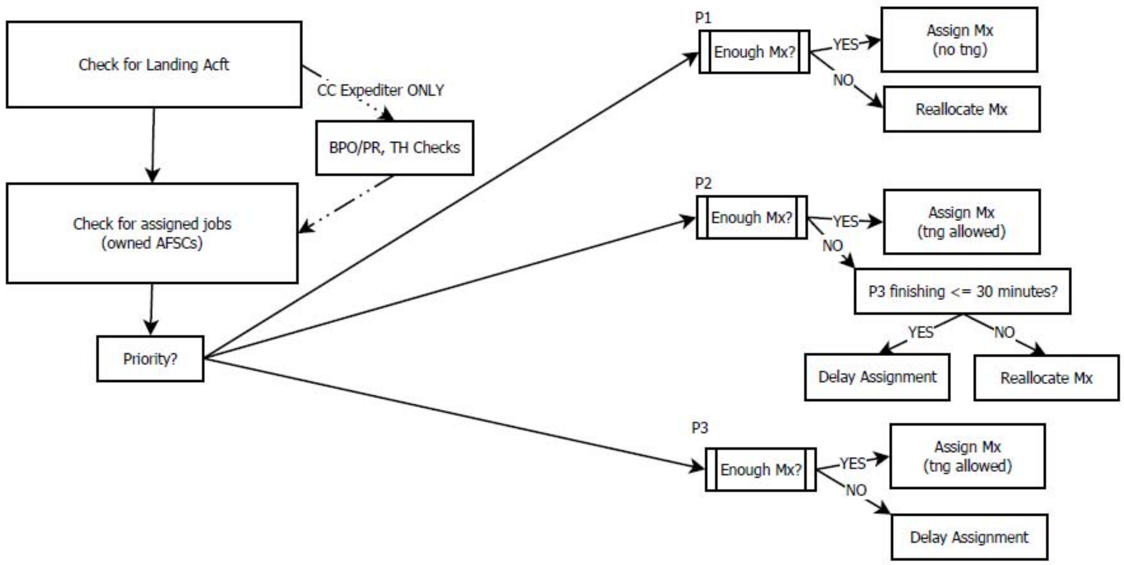

Figure 6 - Expediter Agent Logic

2.2.4 Maintainer Agents

The individual maintainer agents have a minimum of global awareness. Given that the typical maintainer's focus is on fixing, inspecting, or servicing an aircraft, there was no need to model any decision-making capabilities. In effect, each maintainer resides in a ready pool until tasked to a job by their owning expediter. Logic to determine the nature, fix-time, crew size, etc. of the tasks are driven by random draws evaluated against empirical and/or theoretical distributions derived from data gleaned from the CAMS maintenance information system (MIS). When assigned to a job, each individual's efficiency attribute is used to determine the speed at which it is accomplished. An individual agent's efficiency value attribute varies from 0 (no skills) to 1 (highly skilled). This attribute is then increased over time, via a learning curve function developed through interviews with experienced maintainers both in the field and at AFIT. General logic flow is depicted in Figure 7.

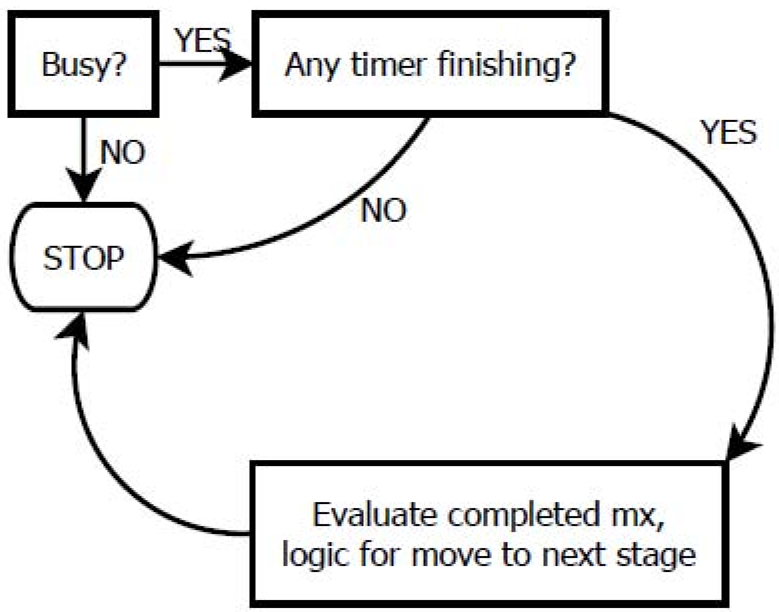

Figure 7 – Maintenance (mx) Agent Logic

2.3 Supporting Data

The sortie generation process is data intensive, even when examined at a aggregate or very top level. As increasing levels of detail were added to each of the agents, requirements for additional data increased. Primary sources included the Logistics Installations and Mission Support Enterprise View (LIMS-EV), and the Global Combat Support System – AF Data Services (GCSS-AF), both web-based tools accessible via the Air Force Portal. Additional data was provided by USAFE/A9, ACC/A4 and interviews with maintainers at both Shaw AFB and Spangdahlem AB. Table 1 lists key data requirements and their sources.

Table 1 - Data Requirements and Sourcing

Data Requirement	Source
# of Aircraft	Spangdahlem AB
# of Personnel	Shaw AFB
Break Rate	LIMS-EV, GCSS
Abort Rate	LIMS-EV, GCSS
Fix Rates	GCSS
Work Unit Code (WUC) Determination	GCSS
AFSC Assignment	GCSS
Crew Size Determination	GCSS
Average Sortie Duration (ASD)	LIMS-EV
Learning curve	Shaw AFB

A large number of discrepancies were noted during collection of the maintenance data from GCSS. Specifically, after collecting data on unscheduled maintenance performed over a two-year time period, almost 30% of the items attributed to one AFSC were actually scheduled inspections that appeared to have been incorrectly coded in the system as unscheduled maintenance tasks. Potential impacts due to constraints on the accuracy of data within automated maintenance information systems have been discussed in other studies (Dahlman et al, 2002). Efforts were made to filter out inconsistencies that were readily apparent, but a key assumption is that the remaining data used in our study is representative of true system behavior and performance.

While in some instances the raw data could be used directly (numbers of aircraft and personnel), in the majority of cases distributions had to either be constructed or fitto the gathered data. This was further delineated into those instances requiring the construction of simple distributions and those requiring the formulation of a more complex conditional structure. Distributions for break and abort rates are examples of the simpler case, where each was represented with a single, simple, theoretical distribution or empirical distribution function. Conversely, WUC determination and fix rates provide an example of the more complex structure. Rather than utilizing a single distribution to characterize a general fix time for each break, the model determines a WUC for each break, a specific AFSC set to work that WUC, and then utilizes a specifically fitted theoretical distribution based on these conditions to calculate a fix time. This multi-tiered approach provides a more realistic portrayal of the process, both in terms of a more accurate depiction of manpower allocation (specific AFSCs) and a fix time associated with that allocation.

Figure 8 provides a graphical depiction of this WUC and AFSC determination process. Entering from the left with a break event, the model first determines the WUC for the aircraft break (region 1). This is accomplished via an empirical distribution function (EDF) built from a two-year sample of data. This data is also situationally dependent; the EDF for breaks determined in flight (air aborts or Code 3 breaks) is different from the distribution used for breaks determined during an inspection or other on-ground maintenance.

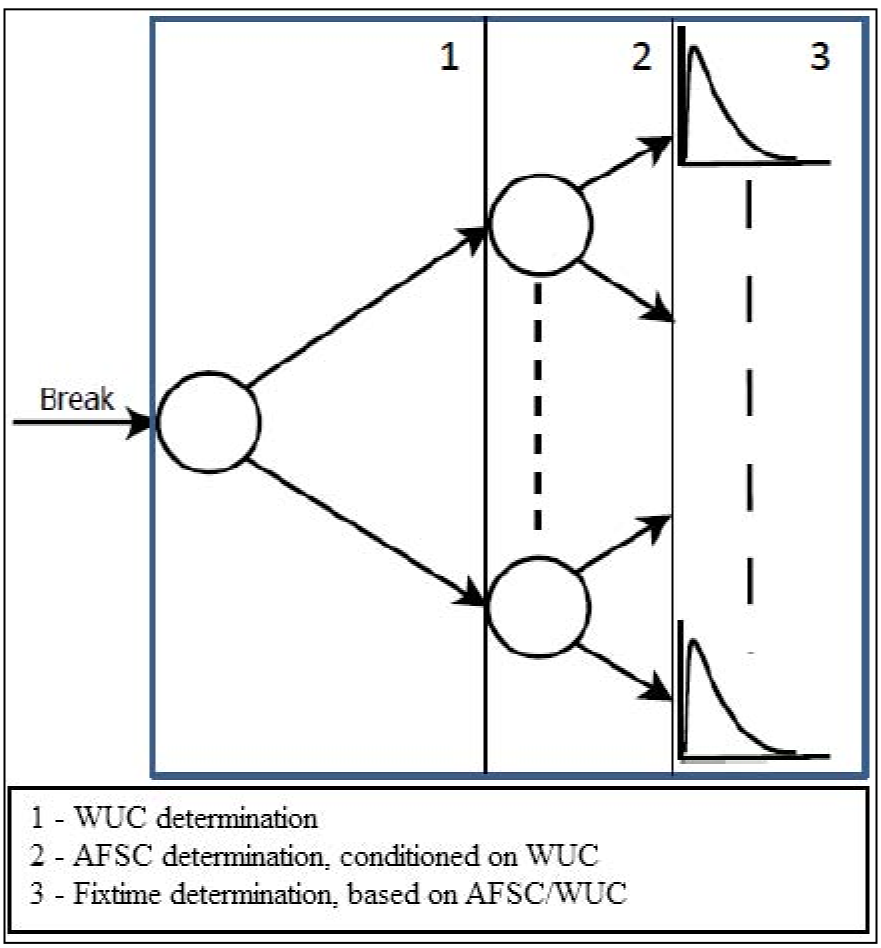

Figure 8 - Determination of WUC and AFSC

The next step is determining the AFSC required to fix this specific break (region 2 in Figure 8). This also uses an EDF, conditional on the pre-determined WUC. The third and final step is the determination of the base fix time (region 3). Each endpoint of this tree structure, representing a specific AFSC and WUC combination, has its own fitted theoretical distribution. The model performs a draw from the specified distribution, is potentially modified depending on the assigned crew's skill level composition and size, and is returned as a final fix time. A similar multi-tiered conditional structure is used for determination of crew sizes for each job. In each case, distributions were based on two years of source data.

While the data-gathering process was by necessity a manual operation, fitting the data to appropriate distributions and placing these into a format usable by the model was automated to as large a degree as possible. Utilizing routines developed in Microsoft Visual Basic for Applications (VBA) from within Microsoft Excel, distributions were calculated and then exported into text files in formats used by the simulation model. EDFs were calculated wholly within the Excel application, while Rockwell Automation Technology's Input Analyzer software was used to determine theoretical distribution parameters and return these to Excel for subsequent formatting and exporting operations.

The only exception to using historical data and the fitting process described above was the development of the learning curve parameters. This data was obtained from interviews with senior maintenance personnel at Shaw AFB, and consisted of estimates of worker efficiency by both AFSC and skill level, along with an estimate of how long it would take to improve that efficiency to a level on par with the next highest skill level. Utilizing manpower availability estimates published in AFI 38-201 (2003), these upgrade times and efficiency figures were used to form linear plots. The slope of each plot was then taken as the efficiency improvement "learning curve" and used to calculate an efficiency improvement at the completion of every maintenance task. This work did not consider loss of learning due to missed training or lack of task accomplishments.

Figure 9 depicts the learning curves calculated for the Avionics AFSC.

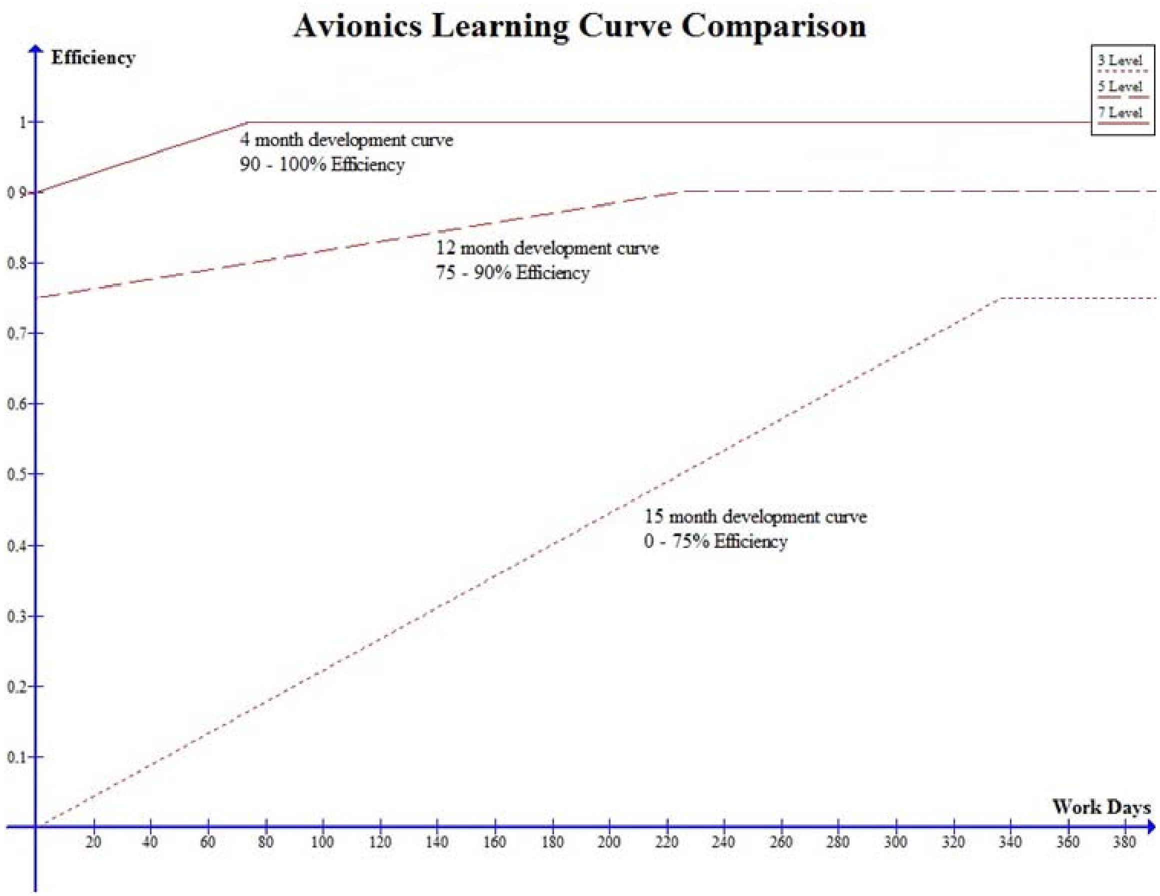

Figure 9 - Avionics Learning Curves

2.4 Logic Development

The final step in the model development was the design and implementation of an overarching construct that established the agents, defined their environment and behaviors, and provided a backdrop to track their iterative execution. Graphical depictions of each agent type's behavior map and accompanying pseudocode were used extensively which, given the simulation's largely modular architecture, significantly aided the development effort.

The remainder of this effort dealt with the addition of supporting logic and routines to manage processes such as shift change, input and output of data, and the establishment of a standard work week and flying schedule. As the model took shape, multiple assumptions had to be made in order to effectively scope the development effort. Significant assumptions and notes on each are listed below:

- Flying window remains constant
    - While the actual schedule changes from day-to-day, the general flying window remains on a day shift.
- Flying load retains a set schedule
    - The sortie load varies from day-to-day but retains a set pattern that repeats from week-to-week.
- Aircraft configuration is not a concern
    - Reconfiguration of aircraft for different missions was not modeled. Based on interviews with maintenance production personnel, it was determined that strict management of aircraft could avoid the majority

of impacts due to aircraft reconfiguration. For purposes of the simulation, it is assumed that aircraft with the correct configuration are assigned to their respective matching mission types.

- Scheduled maintenance is not modeled
    - Since phase inspections are performed outside of the AMU, this process is not modeled. Other scheduled maintenance actions are not included due both to the great number of scheduled inspections and maintenance activities and the lack of specific fix time data for each.
- Overtime is permitted (up to 30 minutes) if agents are working at shift change
    - Rather than attempting to hand over a job near completion, if an agent's estimated time to completion (ETIC) is within 30 minutes at shift change, they continue to work the job until finished
- Aborts and Code 3 breaks result in automatic cancellations of any hot-pit sorties directly following
    - Since aircraft landing Code 3 or Aborting are landing in a non-mission-capable (NMC) status, this forces the cancellation of any follow-on, hot-pit sortie in order to allow maintenance to work the issue.

2.5 Experimental Design and Methodology

The key focus for the analysis with this model was the effects of varied levels of maintenance manpower, both in terms of sortie production and utilization. Specific responses of interest were:

- Daily utilization rates for each AFSC and skill level, and
- Sorties flown and cancelled per week

Factors identified for analysis were the number of personnel within each AFSC. While it is acknowledged that different strategies for allocating personnel across shifts generate significantly different results, the vast number of potential combinations and approaches suggested limiting design complexity. For this research, four aggregated manning factors were utilized, one for each AFSC. Each of these had three levels:

- Base: the typical manning profile based on Shaw AFB's daily manning,
- Reduced: a 10% loss of personnel, and
- Increased: a 10% increase of personnel.

Rather than turn this analysis into an exploration for an optimum AFSC and skill mix for each shift in the face of changing manning availability, both the reduced and increased cases were calculated in as straightforward a manner as possible. Under the assumption that a unit would maintain relatively the same proportions of skills and AFSCs on each shift regardless of manning changes, each shift and AFSC is evaluated individually. As an example, on day shift there are 30 crew chiefs in the base case: 7 three-levels, 14 five-levels and 9 seven-levels. The reduced case then translates to a loss of three crew chiefs on this shift. Using the original proportions of skill levels as a reference (23%, 46% and 30% for three-, five- and seven-levels respectively), these proportions are applied to the reduced shift manning level of 27 crew chiefs. In this example, the reduced levels of manning then equate to 6 three-levels, 13 five-levels and 8 seven-levels.

Despite this clear-cut approach at testing, the running of a complete full 3^4 factorial experiment was estimated to take over fifteen days. However, since cross-utilization training was not modeled (there is no sharing of job taskings between AFSCs), it was believed that none of the identified responses would exhibit significant interactions between any of the experimental factors. To reduce the computational burden but still obtain information on the factors of interest, a fractional factorial screening experiment was employed. Additionally, the factor space was reduced to include only the reduced and increased manning levels, with the base levels used as center points. As suggested in Montgomery (2009), this provides a means to identify curvature (quadratic effects) and test for lack of fit, while simultaneously minimizing the size and design complexity of the overall experiment. This led to the implementation of a resolution IV, 2^{4-1} design with 25 centerpoints used as a screening experiment.

For the execution of the experiment, it was determined that the simulation would run for a total of 210 days. This equated to 7.5 "months" of 28 calendar days (20 working days) each. This temporal abstraction was implemented in the interest of simplicity, as well as to more closely align with standard Air Force availability planning factors of 20.9 assigned days per month (AFI 38-201, 2003). The figure of 7.5 months was selected based on a standard of 6 months for typical manning studies (Juarez, 2010), with additional time added to allow for data truncation. Pre-experiment tests revealed no definitive warm-up period, which was determined most likely to be a result of the cyclical nature of the simulation. However, since time-keeping logic within the model allowed for 6 days of flying the first simulated week, this entire week was truncated prior to commencement of any analysis. A variance assessment was performed on the responses of interest, and it was determined that after 20 replications, variance remained relatively constant; thus, 25 replications per experimental treatment were used.

Initial results from the model were disappointing, portraying utilization rates of less then 1% for many of the specialist AFSCs, and resulting in an almost universal lack of statistical significance in the analysis of variance performed on the experiment results. It was determined that the model's current logic of assigning a single break instance each time that a break was determined to have occurred was the culprit. Since the specialist AFSCs were historically tasked less according to the fitted data, certain AFSCs were not receiving sufficient taskings throughout any day to induce any stress on that specific job type. A modification was made to the logic, enabling a stochastically determined number of break instances to occur each time a break was determined to have happened. Again, two years of data were utilized to form two separate distributions: one for breaks occurring in flight and another for breaks identified during ground inspections.

With these modifications in place, Table 2 depicts the results of the screening experiment, which were somewhat at odds with the original expectations. However, upon further reflection, a plausible explanation was determined.

Table 2 - Screening Test Results

Responses	Significant Factor(s)	Curvature?	Responses	Significant Factor(s)	Curvature?
CC3 UTE	CC, AV Manning	No	EE3 UTE	EE Manning	No
CC5 UTE	CC Manning	Yes	EE5 UTE	CC, AV, EE Manning	No
CC7 UTE	CC, AV Manning	No*	EE7 UTE	EE Manning	Yes
AV3 UTE	AV Manning	Yes	JET 3 UTE	CC Manning	No
AV5 UTE	AV Manning	Yes	JET 5 UTE	JET Manning	No*
AV7 UTE	AV Manning	No	JET 7 UTE	N/A	No
Sorties/Week	N/A*	No	Cancels/Week	N/A*	No

Legend: CC – Crew Chiefs, AV – Avionics, EE – Electro-Environmental, JET – Propulsion
* - P-value for significance (F-test) greater than 0.05, but less than 0.1

First, examine the emergence of multiple significant factors for various individual responses, looking specifically at 3-level crew chief utilization as an example. In this case, it is arguable that even though each AFSC works independently, a significant number of crew chief and avionics jobs might be needed in extended maintenance on broken aircraft, especially if either or both of these manning pools was affected in some manner. This would result in an elevated maintenance priority for aircraft slated to fly, which would then prohibit the completion of any training, the end result being a decrease in the 3-level utilization rate. Similarly, the appearance of some curvature within many of the responses was expected, since reductions or additions to the pool of available manpower should result in the remainder of the available manpower pool working more or less, respectively, in order to keep up. These results allowed for a reduction in scope of the experiment to a 2^4 full factorial, reducing the overall testing to less than a quarter of the initial design expectation.

2.6 Results and Analysis

The running of the remainder of the 2^4 full factorial experiment served to further solidify the assessments made on the initial screening experiment. While certain AFSCs and skill levels exhibited multiple significant factors, each of these is easily attributable to causes similar to that discussed above. Results from the 2^4 full-factorial experiment are included below in Table 3. Changes from the initial screening experiment results are indicated by underlined and italicized text within the table.

Table 3 - Results of Full 2^4 Experiment

Responses	Significant Factor(s)	Curvature?	Responses	Significant Factor(s)	Curvature?
CC3 UTE	CC, *AV** Manning	No	EE3 UTE	EE Manning	No
CC5 UTE	CC Manning	Yes	EE5 UTE	CC, *AV**, EE, *JET** Manning	No
CC7 UTE	CC, *AV** Manning	*Yes*	EE7 UTE	*CC*, *AV*, EE Manning	Yes
AV3 UTE	AV Manning	Yes	JET 3 UTE	*AV*, *JET** Manning	No
AV5 UTE	AV, *JET** Manning	Yes	JET 5 UTE	*CC*, JET Manning	*No*
AV7 UTE	AV Manning	No	JET 7 UTE	*CC** Manning	No
Sorties/Week	*AV* Manning	No	Cancels/Week	*AV* Manning	No

Legend: CC – Crew Chiefs, AV – Avionics, EE – Electro-Environmental, JET – Propulsion
* - P-value for significance (F-test) greater than 0.05, but less than 0.1

Similar to the initial results discussed above, the results indicate a surprising number of relationships between individual AFSCs that were not predicted to have existed. An initial concern was that the results might be due to some invalidity of the fundamental distributional assumptions for the analysis of variance. Other than some slight departures from normality in the tails of the analyzed residuals, however, the underlying assumptions of normally and independently distributed errors with constant variance were verified to hold. Also, as one considers the effects of dynamic reprioritization of maintenance, it becomes easier to visualize that these are the apparent effects of immutable production requirements being levied upon a dynamic grouping of resources. In a "real-world" sense this represents a unit's production staff waging their day-to-day battle of meeting the flying mission while simultaneously attempting to provide sufficient training opportunities to junior troops. As available qualified resources become scarce, they are forced to sacrifice training in order to maintain levels of production necessary to meet mission requirements. The case of the EE5 UTE response provides an excellent illustration of these types of effects and interactions. As evidenced in Figure 10, as individual AFSC manning levels are modified, the resulting effects on EE utilization are unmistakable. Additional details on the analysis performed can be found in Appendix A.

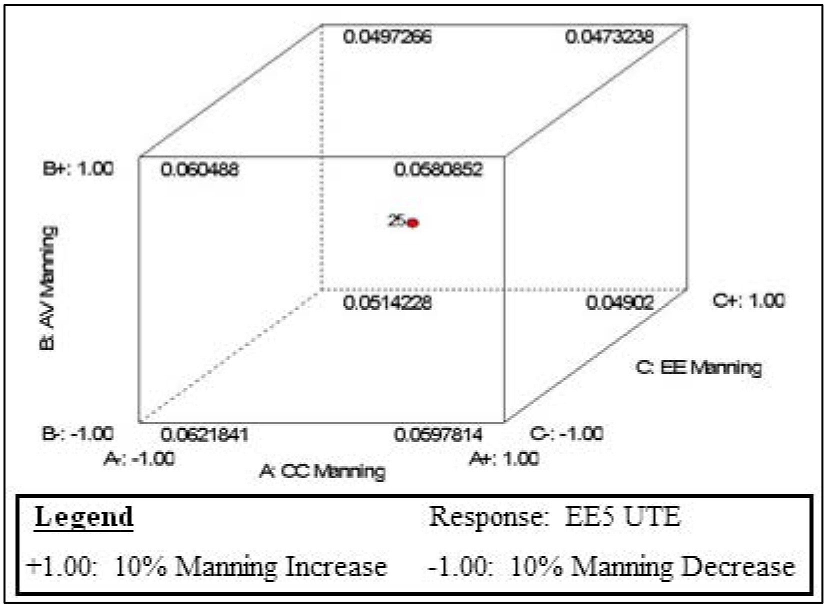

Figure 10 - EE5 UTE Response Values

Figure 11 provides a graphical comparison of weekly cancellations over time between the reduced manning (left) and increased manning (right) scenarios. In the

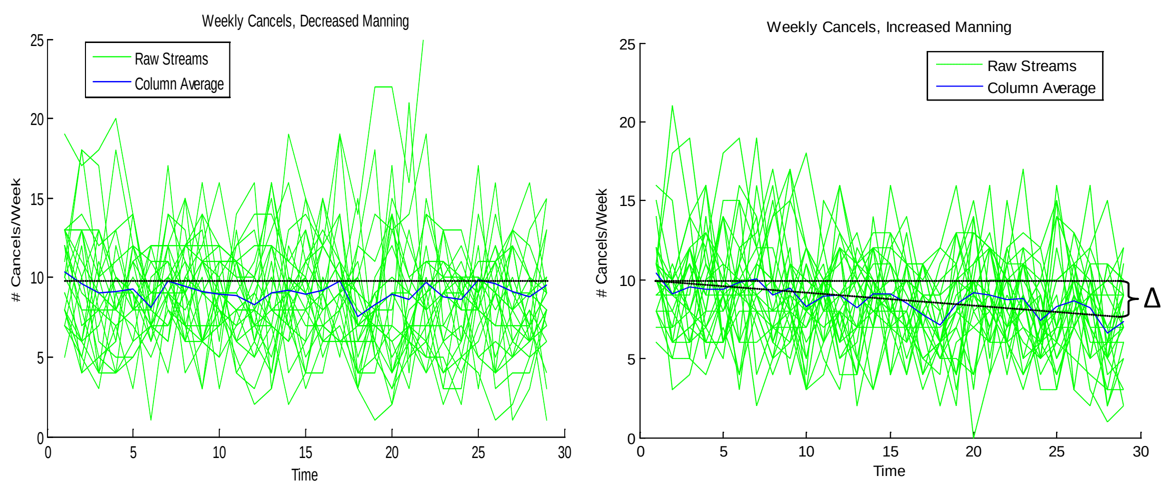

Figure 11 - Comparison of Cancels per Week

reduced case, notice that the slope of the data's average is relatively flat, indicating that maintenance is in "survival mode", essentially striving to maintain one specific level of performance. Conversely, the increased manning scenario provides the capacity for training of junior personnel to occur with greater regularity, which results in a net increase in capacity as the unit's overall average skill level increases. The end result is a decrease in overall cancellations per week as time goes by.

2.7 Conclusions

The nature of the results presented provide a level of fidelity heretofore unavailable from both current and past methodologies surveyed in terms of details on individual skill levels. Since many of the processes external to the core sortie generation process were abstracted out of the model, it might be considered fruitless to conjecture on the efficacy of the specific utilization rates produced by the model. However, considering the model presents a "best case" scenario in which maintenance personnel are required to deal only with the unscheduled maintenance items that crop up on a day to day basis, this model provides significant insight into the relationships between specific AFSCs and skill levels and their effects both on AFSC utilization as well as sortie production capacity.

In summary, it is clear not only that differing mixes of skills within individual AFSCs can exert significant influence on a unit's capacity and capability, but also that the use of an agent base modeling framework is effective in capturing many of the dynamic relationships that drive the complex processes involved in sortie generation.

3. Case Study

Assessing Maintenance Capability

3.1 Introduction

In the summer of 2008, after noticing a highly variant trend in the combat mission readiness (CMR) of his assigned forces, the commander of United States Air Forces in Europe (USAFE) tasked his staff to examine all facets of the CMR process and determine what the major causal factors were (Lipina, 2009). As a result of this tasking, a regression study was completed in 2009 that quantified a variety of factors driving the variation in the CMR metric (Lipina, 2009). Based on the study's results, which were briefed to the Air Force Chief of Staff in the spring of 2009, additional taskings were levied on the operations (AF/A3) and logistics (AF/A4) directorates of the Air Staff. While AF/A3 embarked on an enterprise assessment of the CMR metric's composition, documentation and reporting requirements, AF/A4 was tasked to examine and address the use of aircraft maintenance capability metrics within the Air Force. Specifically, it was identified that no standard definition of maintenance capability existed, and the current methods and models used across the Air Force fail to adequately and convincingly capture the effects of maintenance capability on production capacity (AF/A4L, 2009).

This paper is organized as follows. A brief literature review on related work on maintenance capability and production capacity is provided in Section 3.2. An optimal modeling paradigm is selected and details on its development are provided in Section 3.3.

The prototype model presented provides an original contribution to the current body of research, and analytical results of a simple representative scenario are provided.

3.2 Background

There is a significant body of work that addresses multiple questions surrounding a maintenance unit's capacity and capabilities. This research revealed a string of studies dating back almost 30 years, all focused in some part on a typical maintenance unit's ability to successfully meet its operational requirements. A characteristic theme within all of these studies is a focus and evaluation of the units sortie generation ability. The specific objectives vary greatly, spanning everything from general system observation and characterization to attempts to optimize one or more constituent sub-processes within the overall sortie generation process. These research efforts have employed many methods, including discrete event simulation (Faas, 2003; Iakovidis, 2005), Markov decision analysis (Dietz, 1991) and neural networks (Dagg, 1991). Some of these even specifically addressed the issue of maintenance capability and its potential effects on sortie production and overall readiness (Gotz and Stanton, 1986; Garcia and Racher, 1981). Regardless, the methodologies utilized follow a more traditional approach of decomposing the system under investigation and attempting to describe its behavior as the "sum of its parts", which has been shown to be "inadequate to model and analyze" some large and complex systems (Kaegi et al, 2009). In fact, research performed across multiple disciplines has shown that these traditional methods of system decomposition and subsequent reconstitution can prove not only inadequate but also potentially produce misleading results (Bobashev et al, 2007). Kaegi et al (2009) further argue that in these situations, agent based modeling (ABM) has a “high potential to help realistically model large and complex systems”.

Sortie generation involves an exceptionally complex set of processes with a variety of stochastic elements and external influences. Whether one contemplates the individual electrician or crew chief on the flight line, the supply troop in the Logistics Readiness Squadron, or even individual aircraft or parts being moved up and down the supply chain, each plays a fundamental role in the overall process. Additionally, while the behaviors and motivations of each of these constituent pieces is relatively well understood, the resulting behavior of the system as a whole is more complex than any explanation any individual component could provide. This is the hallmark of a complex system (Flake, 2002), an environment directly suited to an ABM’s ability to reveal “properties of systems that are not properties of the agents themselves” (Jones, 2007).

3.3 An Agent Based Sortie Generation Simulation

Due to the identified complexity of sortie generation, a model of this process would benefit from use of an ABM structure. Looking specifically at the inter-relationships between maintenance personnel across a variety of skill levels and job specialties and their potential outputs in terms of sortie production, an ABM provides a detailed individual-based perspective on the overarching process. The specific focus of this research involves the on-equipment maintenance portion of the sortie generation process. The simulation model is used to examine the effects of various levels of maintenance manning on sortie production and manning utilization while taking into account the specific abilities of individual maintenance personnel across a variety of job specialties and skill levels.

3.3.1 Simulation Model Development

Development of the model required several key assumptions. These were: a) flying window remains constant; b) sortie load retains a set weekly pattern; c) aircraft configuration is not a concern; d) scheduled maintenance is not modeled; and e) collected data used to determine underlying distributions is assumed to be accurate and representative of the underlying real-world systems.

Figure 12 displays a top-level view of the modeled sortie generation process. Within the model, four separate agent types interact according to specific defined behaviors in order to accomplish the tasks making up various portions of the sortie generation process. In brief, the defined agent types are: Production Supervisor, Expediters, Aircraft and Maintenance agents. The Production supervisor provides general oversight and direction to the other agents. The expediter agents allocate personnel to their assigned tasks and are broken down into crew chief, avionics and mechanical (electro-environmental and propulsion) specialties.

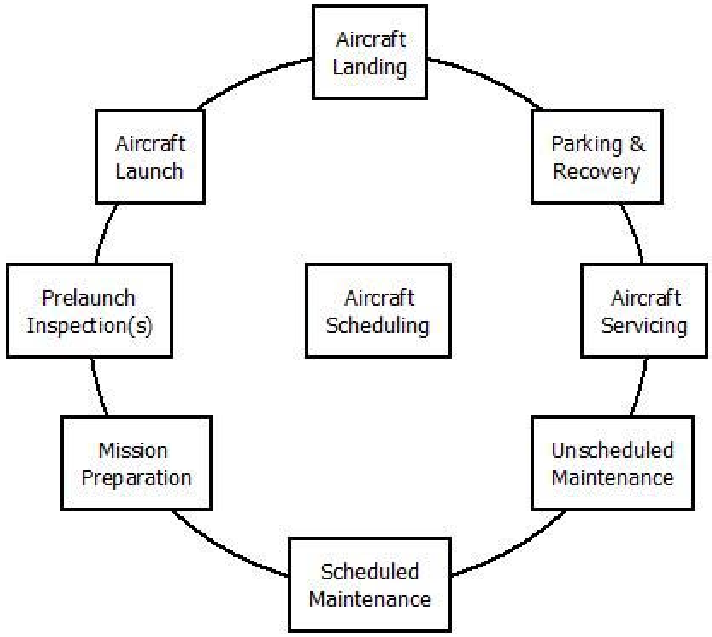

Figure 12 - Modeled Sortie Generation Process

Finally, the maintenance agents serve as assignable resources and are further defined by their AFSC (crew chief, avionics, electro-environmental or propulsion) and skill level (3-, 5- or 7-level). Each of the maintenance agents possesses a learning curve which increases their efficiency (modeled as working speed) over time.

3.3.2 Model Execution

The model begins in an empty and idle state. Following the general outline of the process depicted in Figure 12, a sortie requirement is placed on the system, which results in the assignment of specific aircraft to sorties and an allocation of additional aircraft designated as spares. Jobs are assigned for each of these aircraft, which are in turn assigned to individual maintenance crews by the appropriate expediter. Depending on the priority assigned to each job by the pro super, some jobs are opened as training opportunities for junior (3-level) maintenance troops. As jobs are completed, the released aircraft will fly their assigned sorties, return and be prepped for follow-on missions or receive their end-of-day inspections. This cycle is continuously repeated, with sorties being scheduled 5 days a week, and maintenance crews operating on 3 rotating 8-hour shifts.

Breaks are stochastically determined at various points within the model. Each ground inspection carries a chance to uncover an issue, and each sortie has the potential for either an abort (immediate sortie failure) or Code 3 break (sortie completion, but aircraft lands with maintenance issue). At each of these junctures, a random draw determines the number of issues found, and each of their associated WUCs. All maintenance crew sizes and fixtime lengths for each task are stochastically determined via a multi-branch conditional tree. Conditioned on the identified WUC, separate trees identify both an AFSC and then a fitted theoretical distribution from which a fix time is drawn. Finally, an assessment is made of the assigned team's mean efficiency rating, which is then used to modify the drawn fix time. The net effect is lengthened fix times for lower efficiencies, with the unit's mean efficiency (and thus speed of work) increasing over time as individual maintenance agents learn their jobs. All distributions were based on 2 years of data from Spangdahlem AB, Germany.

3.4 Analysis

This section provides an analysis of the model's output when populated with a typical maintenance unit's maintenance manning levels. An additional response, maintenance efficiency, is also discussed.

3.4.1 Experimental Design

Fourteen core responses were identified as outputs of interest from the model. Twelve responses were the daily utilization rates of each AFSC and skill level, and the final two were the weekly figures for sorties produced and cancellations. An additional set of responses, maintenance efficiencies, were also analyzed. Each agent has a maintenance efficiency varied from 0 (no skill) to 1 (highly skilled). This measured the average increase in efficiency across each AFSC and skill level, capturing the effects of varied manning availability scenarios on the ability of a unit to continue to train and develop its junior maintenance troops. Four factors of interest were identified to drive the experiment: manning levels for each of the four AFSCs modeled. A full-factorial 2^4 experiment was executed. Using a baseline level of manning modeled after data gathered from Shaw AFB as centerpoints, high and low test levels were formulated based on a 10% increase or reduction in available manning for each AFSC.

3.4.2 Results

Test results were based on a run length providing slightly over 7 months of data after deleting the first week. While the majority of AFSCs' learning curves were based on a 12 month developmental cycle, this shorter time span allowed for additional replications and test points while still providing a solid indication of increased proficiency. After some initial testing, it was determined that output variance stabilized after 20 replications; 25 replications per design point was used. Post-test evaluation of the responses indicated no severe departures from normality, so a series of standard ANOVA tests was performed for each of the responses. Results are provided in Table 4.

Table 4 - Experiment Results

Responses	Significant Factor(s)	Curvature?	Responses	Significant Factor(s)	Curvature?
CC3 UTE	CC, AV* Manning	No	EE3 UTE	EE Manning	No
CC5 UTE	CC Manning	Yes	EE5 UTE	CC, AV*, EE, JET* Manning	No
CC7 UTE	CC, AV* Manning	Yes	EE7 UTE	CC, AV, EE Manning	Yes
AV3 UTE	AV Manning	Yes	JET 3 UTE	AV, JET* Manning	No
AV5 UTE	AV, JET* Manning	Yes	JET 5 UTE	CC, JET Manning	No
AV7 UTE	AV Manning	No	JET 7 UTE	CC* Manning	No
Sorties/Week	AV Manning	No	Cancels/Week	AV Manning	No

Legend: CC – Crew Chiefs, AV – Avionics, EE – Electro-Environmental, JET – Propulsion
* - P-value for significance (F-test) greater than 0.05, but less than 0.1

While the results presented in Table 4 are based on the varied numerical results provided from the model, the numbers are not the response of interest. With the variety of abstractions utilized to develop the model, the utility of these numerical responses as point estimators for true system performance is questionable. Instead, the surprising number of dependencies identified between disparate groups of manning is of key interest, chiefly because no interaction between any of these groups was included as a part of the model logic.

Using the EE5 UTE response as an example, the original assumption was that the only factor of significance would be the EE manning pool. However, when one considers that the CC and AV AFSCs received the highest number of taskings, or that the average JET fix times tend to be somewhat lengthy, it is easy to see that modifications to the available manning for any of these AFSCs might drive maintenance timelines. Coupled with the fact that job priorities upgrade automatically if timelines were not being met, and potentially prohibit completion of any training, one can see that this could lead to shortened job times since the trainers (5- and 7-levels) are no longer slowing down work efforts in order to train lower skill-level members.

A separate evaluation was performed on the effects on efficiency gains as a result of differing manning levels. Figure 13 depicts results from the extreme cases, comparing the baseline case to the reduction and addition of 10% for all AFSCs at once. The chart

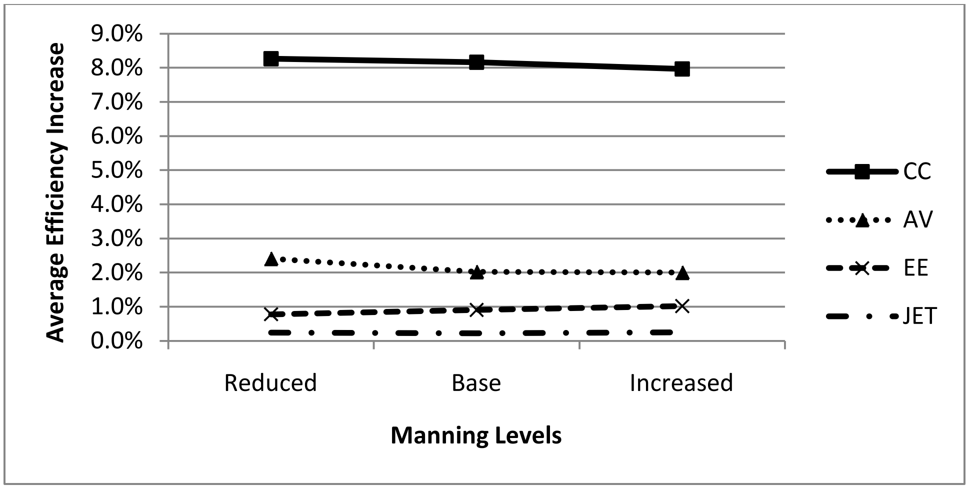

Figure 13 - Comparison of Average 3-level Efficiency Increase

serves as a reminder of the additional complexities within the modeled system. In this case, the seemingly counterintuitive reduction in overall efficiency gains is actually a result of the additional manning added to shifts where work load was not as heavy. As such, these results are largely colored by circumstances peculiar to the simulation, but also underscore the importance of proper shift manning, in addition to the overarching import of sufficient manning levels unit-wide.

3.5 Conclusions

This model and analysis has examined the effects of varied levels of manning availability on both the utilization and production capacity of a maintenance unit. As previously mentioned it is not the intent to assign specific significance to the numerical results presented, but instead to the insight gained on the multiple layers of interactions between the various AFSCs and skill levels in executing the sortie generation process.

The results presented indicate a series of complex interactions between the various groups that make up the primary execution arm of the sortie generation process. Analysis shows that even slight changes in the structure of available manning can have significant effects on a unit's maintenance capacity and ability to develop over time. This has direct implications to any maintenance unit's capability to sustain and support a wing's CMR requirement.

4. Conclusion

4.1 Research Summary

This thesis developed a novel simulation methodology capturing the sortie generation process. It captured the core sortie generation processes and methods, and integrated these within a construct of behavior-driven adaptable entities. This agent based methodology provides details on a variety of system player interactions not available through methods currently being employed.

A representative scenario based on current manning levels and historic maintenance data was performed. While the scope of this prototype model precludes direct validation of the numeric output, accuracy of the internal model logic and behavior models were validated via multiple interviews with career maintenance personnel at Shaw AFB, Wright Patterson AFB and Spangdahlem AB.

4.2 Future Work

An effort is currently underway within the A4 directorate of the Air Staff to examine the methodologies used to model unit level maintenance capacity and capability, and evaluate whether a new method might be warranted. As mentioned in Chapter 2, despite its high level of detail, the LCOM has multiple identified shortcomings that detract from its use for this specific application. This thesis has demonstrated the capability of an agent-based model to capture some of the critical interactions within a unit and their effects on that unit's capacity both to produce and sustain production over time. As a unit's net efficiency changes over time due to retention issues, deployments and permanent changes of station, an understanding of the related potential effects on a unit's capability becomes critical. This is especially true in an era when our end strength is constrained and every unit is expected to do more with less: a skill-balanced force is vital.

The model as presented would definitely benefit from some expansion. Three specific areas identified during the course of model development and analysis were: task detail, scope and the fidelity of agent behavior models. As mentioned in Chapter 2, the questionable validity of available maintenance data makes it difficult to assess the overall validity of the numerical outputs of the model. The LCOM has overcome this in some regards by capturing detailed network flows capturing task level detail for specific jobs down to the 5-digit WUC. Integrating this level of detail into the model would considerably improve the overall validity of the product. Second, having insight into the variety of scheduled inspections performed and the effects on personnel and aircraft availability would add a valuable layer of realism to the model. Finally, while even the simple behavior models in place were shown to be effective, behaviors such as cross-utilization training (maintainers able to work on tasks outside their core AFSC in order to more effectively share work load) would be useful to include, especially as the other two items are addressed, and work load requirements increase accordingly within the model.

Finally, while the model developed for this thesis is easily adaptable to virtually any weapon system within the Air Force inventory, it remains a model of the sortie generation process. However, the same concepts employed can, and have been, employed in a variety of other environments comprised of complex sets of relationships or behaviors. As a sociology tool, it is well-suited to the analysis of human systems. This suggests utility in a variety of manning studies, and is evidenced by a variety of work in this specific area. Recent work of note include Hill and Gaupp's use of agents in modeling the pilot retention problem for the USAF (2006), or a similar study using agents to model the Navy's manpower system (Trifonov et al, 2005).

Appendix A. Analysis Details

This section contains additional details on specific methodology and results employed throughout this thesis. It is separated into developmental and analytical details.

A1. Development Methodology

Any modeling of the sortie generation process becomes a data intensive endeavor. Given the documented difficulties in obtaining "clean" data, great pains were taken to attempt to ensure that the data utilized was as accurate and representative of truth as possible. With the plethora of data available, this involved both the selection of appropriate data, as well as a series of filtering processes.

The first step, data selection, involved choosing the types of data to be included for formulating the variety of distributions required within the model. Data was partitioned based on whether it was a result of a ground-determined or flight-found issue. This partition was enabled through the use of when-discovered (WD) codes contained within the data records. Codes and associated definition for ground-based data are as follows (TO 00-20-7, 2007):

- E – After flight
- F – Between flight – ground crew
- H – Thru-flight inspection
- J – Preflight Inspection

Similarly, for flight-related data, codes and definitions utilized were (TO 00-20-7, 2007):

- C – In-flight, Abort
- D – In-flight, No Abort

The second and final step involved a series of filter operations. After gathering the two macro sets of data, it was discovered that despite having only collected data coded as unscheduled maintenance actions, a great deal of individual records dealt with regularly scheduled inspection items. Luckily, the vast majority of these were coded under a single how-malfunctioned code, used to indicate "how or why a piece of equipment malfunctioned" (TO 00-20-2, 2007). Data was further reduced to remove any record associated with this code. Additionally, there were many cases where multiple records existed for the accomplishment of a single maintenance issue. While in reality this would result from completion of a variety of tasks associated with a single break, the presence of multiple records served to positively bias some AFSCs assignment distributions, while negatively biasing their fix time distribution. Therefore, an automated filter was run through the data set that condensed multiple identical line items (based on individual job control number) into one record, and assigned its fix time as the sum of all constituent records. This served to more effectively capture the time worked *per issue* and avoid the biases previously presented by the data structure.

A2. Analysis Results

Additional numerical results and specific details on the analytic process are included here for completeness. Output analysis methods and ANOVA results are discussed. In the interest of brevity, only a few representative examples are presented.

As previously mentioned, each simulation run provides over 7 months of analyzable data. A month of simulation time was considered to be 4 weeks, or 28 days. While no transient was discerned after evaluating 50 replications of the model, a logic issue allows for flights to occur 6 days over the first week. Thus, data from the first week was truncated, leaving 29 weeks of usable data for subsequent analysis.

Data for each of the responses was first organized to capture the *m* replications of *n* realizations for each of the output sequences $\{X_n : n = 1, 2, 3, \ldots\}$. This yields a matrix of the form

$$\begin{matrix} X_{11} & X_{12} & \ldots & X_{1N} \\ X_{21} & X_{22} & \ldots & X_{2N} \\ \vdots & & & \vdots \\ X_{M1} & X_{M2} & \ldots & X_{MN} \end{matrix}$$

In the case of the 12 AFSC and skill level UTE responses, since the daily UTE rate was more of a concern than the weekly rate, Welch's method of replications (Welch, 1983) was applied, yielding a grand mean for the entire data set representing the average daily utilization rate for each AFSC and skill level. A similar method was employed for the collected flight data, but calculated so as to provide an average weekly figure for each.

ANOVA tests were performed for each of the identified responses. An excellent illustrative example is the 5-level EE UTE response (EE5 UTE). Since the primary interest was in identifying significant interactions between agents within the model, no specific level of α was selected for evaluation of the model. Instead, those items determined significant at the α=.05 level were immediately marked as significant, while those significant at the α=0.1 level were considered within a range of significance of interest to this analysis. The p-values for factors qualifying under the former criteria are highlighted in Table 5 below, while those qualifying at the latter criteria are marked with an asterisk.

Table 5 - EE5 UTE ANOVA Results

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	0.013	4	3.18E-03	36.48	< 0.0001
A-CC Manning	*5.77E-04*	*1*	*5.77E-04*	*6.62*	0.0105
B-AV Manning	*2.88E-04*	*1*	*2.88E-04*	*3.3*	0.0701*
C-EE Manning	*0.012*	*1*	*0.012*	*132.69*	< 0.0001
D-JT Manning	*2.91E-04*	*1*	*2.91E-04*	*3.34*	0.0684*
Curvature	9.87E-05	1	9.87E-05	1.13	0.2883
Residual	0.037	419	8.73E-05		
Lack of Fit	*8.18E-04*	*11*	*7.44E-05*	*0.85*	0.5915
Pure Error	*0.036*	*408*	*8.76E-05*		
Cor Total	0.049	424			

Critical ANOVA assumptions of error normality, independence and constant variance were investigated as a portion of the analytical process. Various diagnostic residual plots are included in Figures 14 through 16 in the interest of thoroughness.

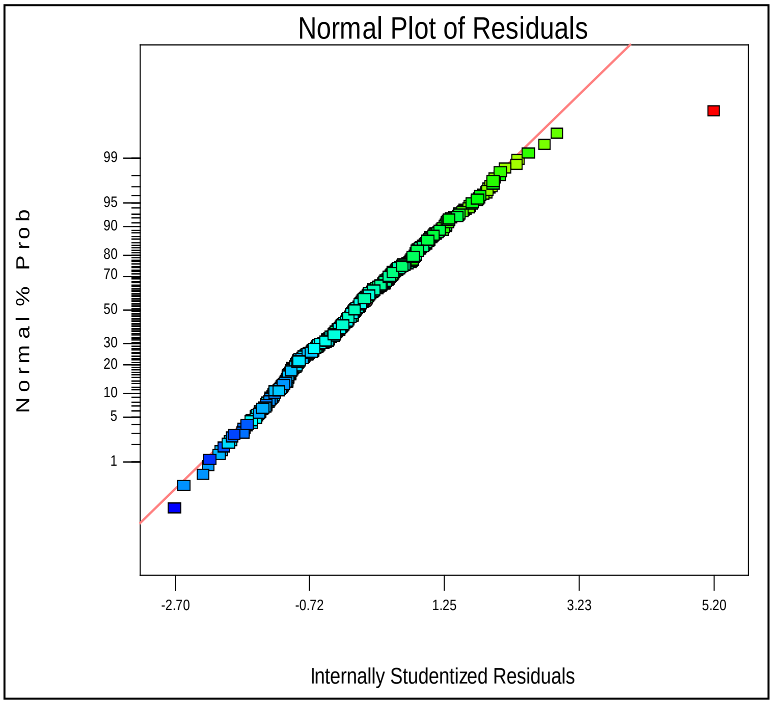

Figure 14 - EE5 UTE Normal Probability Plot

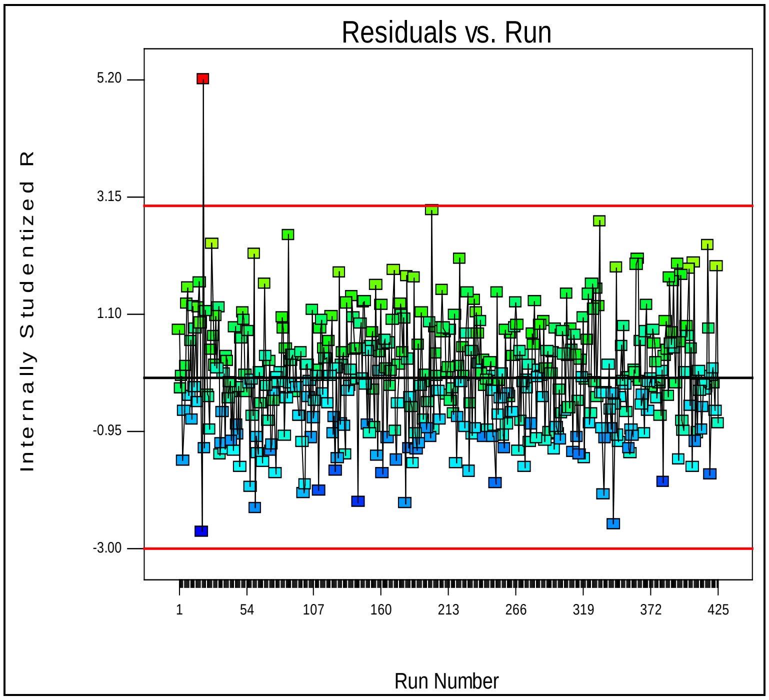

Figure 15 – EE5 UTE Residuals vs. Run

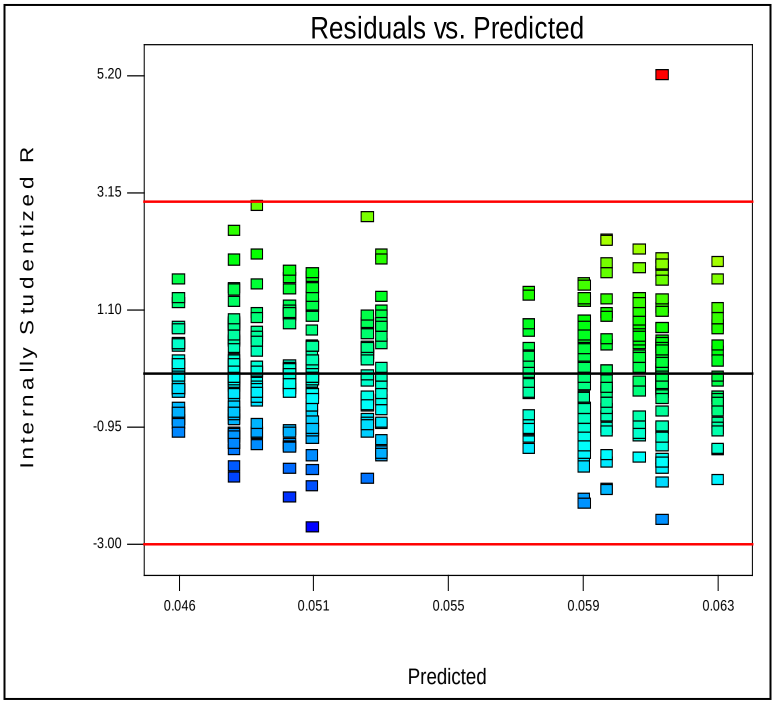

Figure 16 - EE5 UTE Residuals vs. Predicted

The above series of figures indicate all of the model assumptions hold. Of interest is the apparent outlier present on each of the figures. After debating whether or not to remove this datapoint from the overall dataset, it was decided to leave it in place. Since it was one of the initial runs, presenting the worst case scenario with all AFSCs reduced by 10%, it was felt that this portrayed the very real potential for a “snowball effect”. This occurs when a series of bad breaks within a unit’s fleet of aircraft end up overwhelming a unit’s ability to maintain their current production rate. Since the potential for this to occur would be increased by a loss in manning, it was felt that this point, although a statistical outlier, was indicative of potential system performance.

The results indicate a surprising level of interconnectedness between each of the AFSCs. While the operational implications and potential causes were discussed, it is useful to examine these results from a more objective standpoint. It is relatively trivial to understand the high level of significance attributed to EE manning.

Conversely, the factor with the next highest level of significance, crew chiefs, might initially be surprising to see. However, one must consider that crew chiefs are the highest tasked AFSCs within the model, receiving an expected 43% of ground-found tasks and 58% of flight-determined tasks. With high levels of taskings, changes in available crew chief manning has the ability to affect the priority of maintenance within the model, which could then affect whether training is a possibility. This could directly affect the utilization rates of 5-level EE troops, who as qualified maintainers serve as trainers within their AFSC, and would therefore work slower or faster (on average) depending on whether they were involved in training or not. Similar arguments can be postulated for the other factors of significance.

To determine which experimental treatments exhibited significance for each response, a comparison of each of the experiment treatments was made to the baseline (centerpoints). Using Dunnett's test as outlined in Montgomery (2009), the test evaluates the hypothesis

$$H_0: \mu_i = \mu_a$$

$$H_1: \mu_i \neq \mu_a$$

for some i = 1, 2, …, a-1. For this case, the centerpoint treatment mean was treated as the control to which the remaining treatment means were compared.

Table 6 provides a partial set of results from the test. Each of the figures represents the baseline treatment mean subtracted from a specific treatment mean. Significant items (at the α=.05 level) are depicted in bold. With the crew chief responses, almost every single treatment was indicated as significantly different from the baseline treatment. This would imply that this AFSC is volatile in terms of its utilization rate, responsive to even very small changes in manning allocations. As you move to the right within the table, you can see that there is less significance indicated for the avionics AFSC. We postulate that this is due primarily to the difference in the level of taskings between these two AFSCs, with avionics receiving 5-25% fewer taskings than crew chiefs depending on the source of the break. This is supported by the fact that the other AFSCs responses, which jointly account for 16% and 9% of ground and flight taskings, respectively, exhibit almost no significance due to this test.

Table 6 - Results of Dunnett's Test

Treatment	CC3	CC5	CC7	AV3	AV5	AV7
1	0.003838	**0.045307**	**0.037123**	**0.012954**	0.005724	**0.012893**
2	0.007201	**0.039957**	**0.039339**	**0.0144**	0.006188	**0.014324**
3	**0.007885**	**0.044204**	**0.039502**	**0.011525**	**0.009378**	**0.016102**
4	**0.007566**	**0.045523**	**0.037383**	**0.014716**	0.004258	**0.013049**
5	0.005025	**0.052863**	**0.036039**	0.001286	**0.021979**	**0.015769**
6	0.007066	**0.043567**	**0.045657**	0.002579	**0.022144**	**0.014941**
7	**0.012893**	**0.046145**	**0.041664**	0.000232	**0.019682**	**0.013918**
8	**0.009032**	**0.042881**	**0.045638**	0.00237	**0.021737**	**0.014137**
10	**0.008953**	**0.037366**	**0.025625**	**0.014952**	**0.007881**	**0.015579**
11	**0.008469**	**0.034808**	**0.029719**	**0.008811**	0.001719	**0.011289**
12	**0.011369**	**0.032867**	**0.032721**	**0.012128**	0.004517	**0.01289**
13	**0.009914**	**0.033655**	**0.029855**	**0.01051**	0.003939	**0.013521**
14	0.005448	**0.035527**	**0.027269**	0.001314	**0.020217**	**0.015094**
15	**0.008625**	**0.035221**	**0.027366**	0.002627	**0.021216**	**0.01489**
16	**0.009233**	**0.032295**	**0.030219**	0.000935	**0.022479**	**0.016641**
17	**0.008689**	**0.033102**	**0.029364**	0.000951	**0.021372**	**0.012945**

Specific point estimates for each of the responses returned from the model were not of particular interest to the analysis. Utilization rates ranged from roughly 30% in the case of crew chiefs, steadily dwindling to under 2% for jet troops. This was not surprising due to the scoping of the model effort, which was focused more on determining the existence and effects of the interactions between the various agents.

Appendix B. Selected Analysis Results

This section contains a selection of results from the ANOVA performed on each of the 14 responses of interest. While not specifically included, note that all necessary assumptions of residual normality, independence and constant variance were verified to have been met. Full results are available upon request from Dr. Miller in AFIT/ENS.

Table 7 - CC3 UTE ANOVA Results

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	0.027282	4	0.00682	80.07862	< 0.0001
A-CC Manning	0.026898	1	0.026898	315.8082	< 0.0001
B-AV Manning	0.000317	1	0.000317	3.717429	0.0545
C-EE Manning	6.67E-05	1	6.67E-05	0.783672	0.3765
D-JT Manning	4.41E-07	1	4.41E-07	0.005177	0.9427
Curvature	9.55E-06	1	9.55E-06	0.112144	0.7379
Residual	0.035687	419	8.52E-05		
Lack of Fit	0.001386	11	0.000126	1.498928	0.1289
Pure Error	0.034301	408	8.41E-05		
Cor Total	0.062979	424			

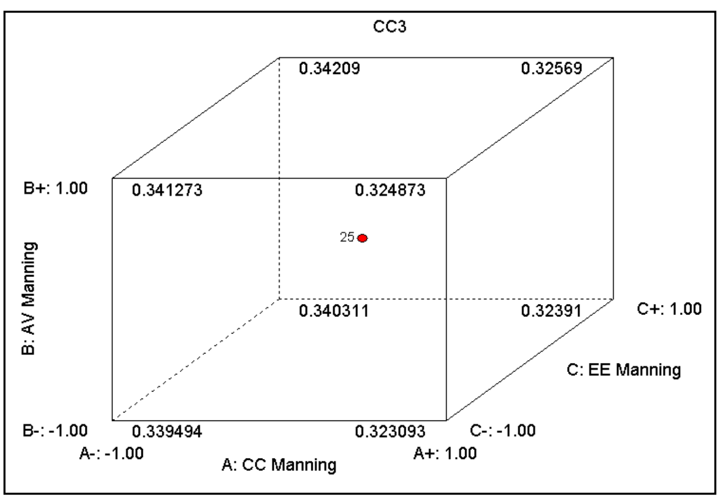

Figure 17 - CC3 UTE Cube Plot

Table 8 - AV7 UTE ANOVA Results

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	0.081267	4	0.020317	282.4728	< 0.0001
A-CC Manning	2.37E-05	1	2.37E-05	0.329299	0.5664
B-AV Manning	0.08121	1	0.08121	1129.103	< 0.0001
C-EE Manning	3.21E-05	1	3.21E-05	0.44582	0.5047
D-JT Manning	9.35E-07	1	9.35E-07	0.013003	0.9093
Curvature	6.94E-06	1	6.94E-06	0.096446	0.7563
Residual	0.030136	419	7.19E-05		
Lack of Fit	0.000603	11	5.48E-05	0.756745	0.6834
Pure Error	0.029534	408	7.24E-05		
Cor Total	0.11141	424			

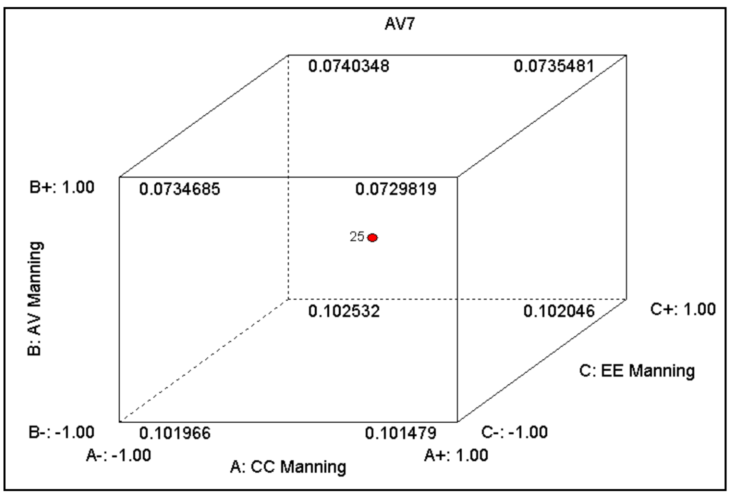

Figure 18 - AV7 UTE Cube Plot

Table 9 - EE3 UTE ANOVA Results

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	0.004876	4	0.001219	38.13561	< 0.0001
A-CC Manning	7.04E-05	1	7.04E-05	2.200973	0.1387
B-AV Manning	3.22E-05	1	3.22E-05	1.007541	0.3161
C-EE Manning	0.004765	1	0.004765	149.0663	< 0.0001
D-JT Manning	8.56E-06	1	8.56E-06	0.267653	0.6052
Curvature	7.17E-06	1	7.17E-06	0.224383	0.6360
Residual	0.013393	419	3.2E-05		
Lack of Fit	0.000564	11	5.13E-05	1.631055	0.0875
Pure Error	0.012829	408	3.14E-05		
Cor Total	0.018276	424			

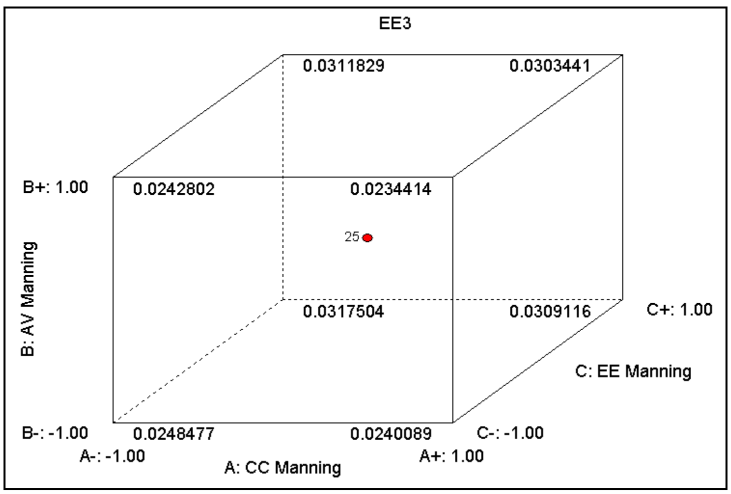

Figure 19 - EE3 UTE Cube Plot

Table 10 - JET5 UTE ANOVA Results

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	0.001583	4	0.000396	11.20796	< 0.0001
A-CC Manning	0.00014	1	0.00014	3.975037	0.0468
B-AV Manning	8.68E-06	1	8.68E-06	0.245764	0.6203
C-EE Manning	4.94E-05	1	4.94E-05	1.400068	0.2374
D-JT Manning	0.001385	1	0.001385	39.21098	< 0.0001
Curvature	9.4E-05	1	9.4E-05	2.663038	0.1035
Residual	0.014795	419	3.53E-05		
Lack of Fit	0.000112	11	1.02E-05	0.282918	0.9888
Pure Error	0.014683	408	3.6E-05		
Cor Total	0.016473	424			

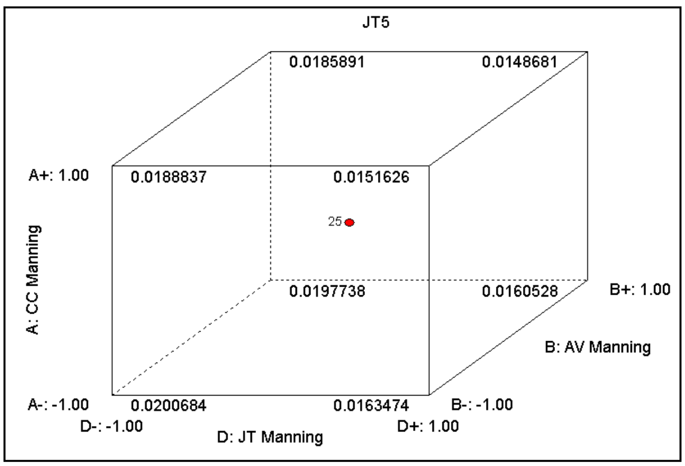

Figure 20 - JET 5 UTE Cube Plot

Table 11 - Sorties ANOVA Results

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	9.173227	4	2.293307	2.022795	0.0904
A-CC Manning	0.982223	1	0.982223	0.866363	0.3525
B-AV Manning	6.011253	1	6.011253	5.302184	0.0218
C-EE Manning	0.665973	1	0.665973	0.587417	0.4439
D-JT Manning	1.513779	1	1.513779	1.335218	0.2485
Curvature	0.871103	1	0.871103	0.76835	0.3812
Residual	475.0335	419	1.133731		
Lack of Fit	7.087663	11	0.644333	0.561791	0.8596
Pure Error	467.9458	408	1.146926		
Cor Total	485.0778	424			

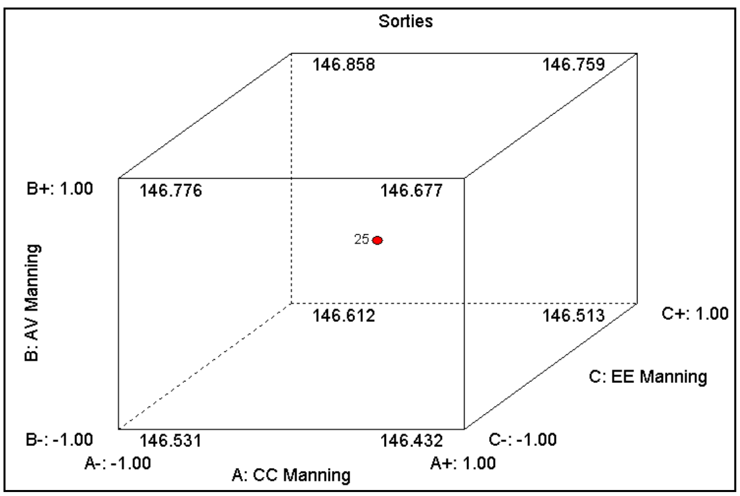

Figure 21 - Sorties Cube Plot

Table 12 - Cancels ANOVA Results

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob > F
Model	10.24565	4	2.561413	2.86	0.0233
A-CC Manning	1.186543	1	1.186543	1.32486	0.2504
B-AV Manning	6.685918	1	6.685918	7.465306	0.0066
C-EE Manning	0.692462	1	0.692462	0.773183	0.3797
D-JT Manning	1.680727	1	1.680727	1.876652	0.1714
Curvature	0.809965	1	0.809965	0.904384	0.3422
Residual	375.2559	419	0.895599		
Lack of Fit	6.54852	11	0.59532	0.658763	0.7775
Pure Error	368.7073	408	0.903694		
Cor Total	386.3115	424			

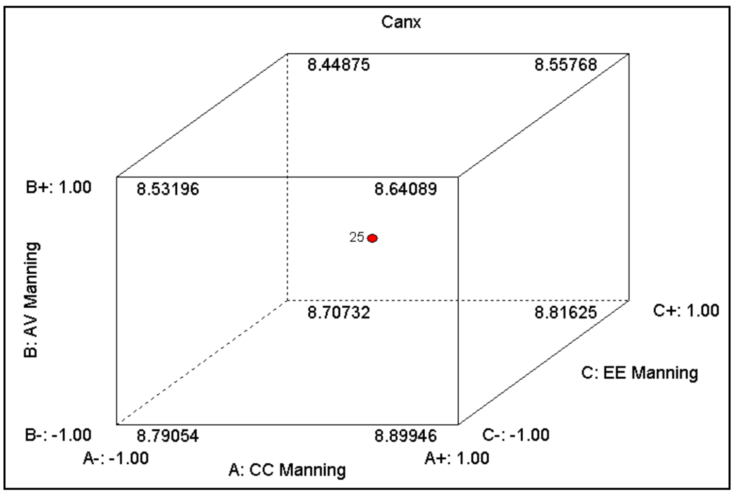

Figure 22 - Cancels Cube Plot

Appendix C. Blue Dart

Improving Assessments of Maintenance Capacity and Capability

The ultimate source of combat capability resides in the men and women of the Air Force

\- (AFDD1, 2003)

"Do more with less" sums up the current operating environment. With fiscal constraints driving hard decisions, balancing various requirements in manpower, materiel and weapon systems, Air Force leaders are forced to rely on a variety of projections and analyses detailing the trade-offs inherent in each potential choice. Each decision carries a spectrum of ramifications, with impacts spanning the gamut from fiscal to readiness.

In recent years, the Air Force experienced a series of manning cuts as a result of Program Budget Decision 720 (PBD 720). These were later shown to have been ineffective in achieving their goal of producing savings to finance a recapitalization of the Air Force fleet (Holmes, 2009). The resulting net loss in experience within the enlisted aircraft maintenance fields was irreparable in any immediate sense, addressable only through an increase in enlistments and a flooding of the training pipelines with new maintainers. This supported goals for an increased end-strength, but was unable to address the issue of lost maintainer experience.

What effect does such a shift in a maintenance unit's net experience level have on its capacity to safely and effectively produce sorties and maintain sufficient fleet health and availability to meet ongoing mission requirements? If the experience loss is restrained to a specific career field, do the effects remain localized to that field, or are they dispersed across the unit?

Currently, the Air Force relies on the Logistics Composite Model (LCOM) to provide an answer to questions surrounding maintenance manpower. While LCOM is an extremely detailed and powerful analytical tool, one of its identified shortcomings is its failure to address issues associated with individual skill levels of personnel, to include time spent in training junior personnel and any effects due to differences in worker skill levels. This research focused on applying a new modeling methodology to the sortie generation scenario while specifically capturing a variety of details associated with the effects of individual skill levels. A key feature of the model is that training activities are considered which can cause individual maintenance tasks to take longer, with this effect being mitigated over time as each individual gains experience. The concept of individual development is another central model tenet; each maintainer modeled increases their job efficiency over time according to a skill-level and career-field-specific learning curve.

The prototype model developed through this research indicated a surprising amount of interconnectedness between disparate career fields within a typical maintenance unit. Additionally, there was an indication that a unit's capacity for sortie production was directly tied not only to the number of personnel within the unit but also to the skill- and career-field mix.

With a constant charge to maintain capability while ensuring an overall economy of force, leadership must be able to make informed decisions on the size and shape of our fighting force. End strength is important, but this raw number is an incomplete measurement. Gaining and leveraging an understanding of the range of effects resulting from these underlying personnel interactions is critical in ensuring we remain postured as the world's foremost Air Force.

APPENDIX D. Summary Chart

Bibliography

1. Air Force Personnel Center. *Air Force Enlisted Classification Directory.* Randolph AFB: October, 2009.

2. Air Force Personnel Center. *Interactive Demographics Analysis System.* User-driven Personnel Report Database. Retrieved November, 2009, from http://ask.afpc.randolph.af.mil/

3. Bobashev, Georgiy V., D. Michael Goedecke, Feng Yu, and Joshua Epstein. "A Hybrid Epidemic Model: Combining the Advantages of Agent-based and Equation-based Approaches," *Proceedings of the 39th Conference on Winter Simulation: 40 Years! The Best Is Yet to Come*. 1532-1537. Piscataway, NJ: IEEE Press, 2007.

4. AF/A4L, Minutes of the Operational Maintenance Capability and Capacity Modeling (OMC2M) Workshop, Langley AFB, 15-17 December 2009.

5. Bonabeau, Eric. "Agent-based Modeling: Methods and Techniques for Simulating Human Systems," *Proceedings of the National Academy of Sciences of the United States of America,* 99(10), 7280-7287, 2002.

6. Chimka, Justin R. and Heather Nachtmann. "Operational Readiness as a Function of Maintenance Personnel Skill Level," *Air Force Journal of Logistics,* 31(3): 45-51 (Fall 2007).

7. Ciarallo, Frank W., Raymond R. Hill, Siriam Mahadevan, Vikrant Chopra, Patrick J. Vincent and Chris S. Allen. "Buldin the Mobility Aircraft Availability Forcasting (MAAF) Simulation Model and Decision Support System." *Journal of Defense Modeling and Simulation,* 2(2), 57-69, 2005.

8. Dagg, James M. *An Exploratory Application of Neural Networks to the Sortie Generation Forecasting Problem.* MS Thesis, AFIT/GLM/LSM/91S-11. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright Patterson AFB OH, September 1991 (ADA246626).

9. Dahlman, Carl J., Robert Kerchner, and David E. Thaler. *Setting Requirements for Maintenance Manpower in the U.S. Air Force*. Contract F49642-01-C-0003. Santa Monica CA: RAND Corporation, 2002.

10. Department of the Air Force. *Air Force Basic Doctrine.* AFDD 1. 17 November 2003.

11. Department of the Air Force. *Aircraft and Equipment Maintenance Management*. AFI 21-101. 29 June 2006.

12. Department of the Air Force. *Determining Manpower Requirements*. AFI 38-201. 30 December 2003.

13. Department of the Air Force. *Flying Operations.* AFI 11-2F-16V1. 19 January 2007.

14. Department of the Air Force. *Air Force Posture Statement.* 19 May 2009.

15. Department of the Air Force. *Classifying Military Personnel (Officer and Enlisted).* AFI 36-2101. 1 June 2009.

16. Department of the Air Force. *Maintenance Data Documentation.* TO 00-20-2. 15 April 2007.

17. Dietz, Dennis C. *Optimal Specialization and Allocation of Maintenance Manpower.* PhD Dissertation. The Pennsylvania State University, University Park PA, 1991 (ADA243602).

18. Engleback, Nicholas, Mark Anderson and John Wasser. "Some Uses of Agent-Based Models in the New Zealand Defense Force: Collaboration, Operations, Integration" in *Maneuver Warfare Science.* Quantico, VA: USMC Project Albert. 2003.

19. Faas, Paul D. *Simulation of Autonomic Logistics System (ALS) Sortie Generation*. MS Thesis, AFIT/GOR/ENS/03-07. School of Engineering and Management, Air Force Institute of Technology (AU), Wright Patterson AFB OH, March 2003 (ADA413196).

20. Flake, Gary W. "The Computational Beauty of Nature." Excerpt from published book. http://mitpress.mit.edu/books/FLAOH/cbnhtml/parts.html. November, 2002.

21. Franklin, Stan, and Art Graesser. "Is it an Agent, or Just a Program?: A Taxonomy for Autonomous Agents." in *Intelligent Agents III: Agent Theories, Architectures, and Languages.* Ed. Michael Woodridge. Berlin: Springer-Verlag, 1997.

22. Garcia, Robert, and Joseph P. Racher. *An Investigation Into a Methodology to Incorporate Skill Level Effects Into the Logistics Composite Model.* MS Thesis, AFIT/LSSR/81. School of Systems and Logistics, Air Force Institute of Technology (AU), Wright Patterson AFB OH, June 1981 (ADA105131).

23. Gilbert, Nigel, and Pietro Terna. "How to Build and Use Agent-based Models in Social Science". Unpublished article. http://web.econ.unito.it/terna/deposito/gil_ter.pdf , 18 May 1999.

24. Gotz, Glen A., and Richard E. Stanton. *Modeling the Contribution of Maintenance Manpower to Readiness and Sustainability.* Contract MDA903-85-C-0030. Santa Monica, CA: RAND Corporation, January 1986.

25. Grimm, Volker, Uta Berger, Donald L. DeAngelis, J. Gary Polhill, Jarl Giske, and Steven F. Railsback. "A Standard Protocol for Describing Individual-based and Agent-based Models." Unpublished manuscript. http://www.ufz.de/index.php?de=10466, 2006.

26. Hill, Raymond R and Martin P. Gaupp. "Visualization Tools for Prescriptive Analysis of a Complex Adaptive System Model of Pilot Retention." *International Journal of Modeling and Simulation*, 6(4), 378 – 384, 2006.

27. Holmes, Eric. "Wynne: Drawdown Needs to Stop after 2009 Cuts". *Air Force Times.* 26 September, 2009. http://www.airforcetimes.com/news/2007/09/airforce_forcesize_070924/

28. Iakovidis, Konstantinos. *Comparing F-16 Maintenance Scheduling Philosophies*. MS Thesis, AFIT/GLM/ENS/05-12. School of Engineering and Management, Air Force Institute of Technology (AU), Wright Patterson AFB OH, June 2005 (ADA436130).

29. Jones, Gregory T. "Agent-based Modeling: Use with Necessary Caution." *American Journal of Public Health, 97*(5): 780-781 (May 2007).

30. Juarez, Fred. LCOM Program Manager, Air Force Manpower Agency. Telephone interview. 28 January 2010.

31. Kaegi, M., R. Mock, and W. Kroger. "Analyzing Maintenance Strategies by Agent-based Simulations: A Feasibility Study." *Reliability Engineering and System Safety, 94*(9): 1416-1421 (September 2009).

32. Krishnamurthy, Prashanth, Farshad Khorrami, and David Schoenwald. "Decentralized Inventory Control for Large-Scale Reverse Supply Chains: A Computationally Tractable Approach." *IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews, 38*(4): 551-561 (July 2008).

33. Law, Averill. *Simulation Modeling and Analysis* (4th ed.). New York, NY: McGraw Hill, 2007.

34. L'Ecuyer, Pierre. "Software for Uniform Random Number Generation: Distinguishing the Good and the Bad." *Proceedings of the 2001 Winter Simulation Conference,* 1: 95-105 (December 2001).

35. Lipina, Andrew J. *Identifying Critical Factors Affecting Combat Mission Ready Status Among USAF Europe's Aircrew.* Graduate Research Project, AFIT/IOA/ENC/09-01. School of Engineering and Management, Air Force Institute of Technology (AU), Wright Patterson AFB OH, June 2009.

36. Macal, Charles M., and Michael J. North. "Tutorial on Agent-based Modeling and Simulation." *Proceedings of the 37th Conference on Winter Simulation,* 2-15, December 2005.

37. Matsumoto, Makoto, and Takuji Nishimura. "Mersenne Twister: A 623-dimensionally Equidistributed Uniform Pseudo-random Number Generator." *ACM Transactions on Modeling and Computer Simulation, 8*(1): 3-30 (1998).

38. Montgomery, Douglas C. *Design and Analysis of Experiments* (7th ed.). Hoboken, NJ: John Wiley and Sons, 2009.

39. Project Albert. "Project Albert". http://www.projectalbert.org/index.html . 3 February 2010.

40. Railsback, Steven F., Steven L. Lytinen, and Stephen K. Jackson. "Agent-based Simulation Platforms: Review and Development Recommendations." *Simulation, 82*(9): 609-623 (September 2006).

41. Tripp, Robert S., Mahyar A. Amouzegar, Ronald G. McGarvey, Rick Bereit, David George, and Joan Cornuet. *Sense and Respond Logistics: Integrating Prediction, Responsiveness and Control Capabilities*. Contract F49642-01-C-0003. Santa Monica, CA: RAND Corporation (2006).

42. Trifonov, Iavor, Oliver Bandte, Eric Bonabeau, and Paolo Gaudiano. *Agent-Based Modeling as a Tool for Manpower and Personnel Management*. Cambridge, MA: Icosystem Corporation (June 2005).

43. Welch, Peter D. The Statistical Analysis of Simulation Results. In *The Computer Performance Modeling Handbook,* ed. S. Lavenburg, 268-328. New York: Academic Press. 1983.

44. Wilensky, Uri. *NetLogo*. Version 4.1RC3, Windows. Computer software. Center for Connected Learning and Computer-Based Modeling, Northwestern University, Evanston, IL. Available at http://ccl.northwestern.edu/netlogo/, 1999.

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14. ABSTRACT

Agent based models have been shown to be powerful tools in describing processes and systems centered on individual behaviors and local interactions (i.e. "bottom-up") between specific entities. Current application areas tend to be focused within the business and social science arenas, although their usefulness has been demonstrated in the modeling of various chemistry and physics-based systems.

Conversely, many highly process-oriented systems, such as manufacturing environments, tend to be modeled via "top-down" methods, including discrete or continuous event simulations among others. As a result, potentially critical attributes of the entities or resources modeled with these methods (spatial properties, "learning curve" or adaptability) may not be adequately captured or developed. This research develops an agent based model for application to a problem heretofore addressed solely via discrete event simulation or stochastic mathematical models. Specifically, a model is constructed to investigate the effects of differing levels of maintenance manning on sortie production capability, with an examination of those effects on the resulting Combat Mission Readiness (CMR) of a typical F-16 squadron.

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